



# Model-based Programming as Estimating, Planning and Executing based on Hidden State

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IS Program Review

September 5<sup>th</sup>, 2002

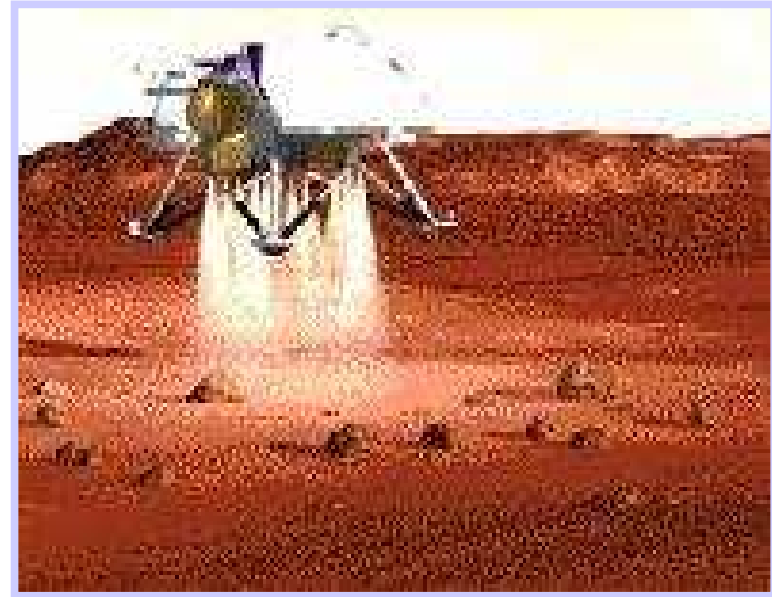
# Why Model-based Programming?

Polar Lander Leading Diagnosis:

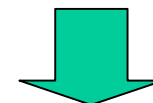
- Legs deployed during descent.
- Noise spike on leg sensors latched by software monitors.
- Laser altimeter registers 50ft.
- Begins polling leg monitors to determine touch down.
- Latched noise spike read as touchdown.
- Engine shutdown at ~50ft.



Programmers often make commonsense mistakes when reasoning about hidden state.



Objective: Support programmers with embedded languages that avoid these mistakes, by reasoning about hidden state automatically.



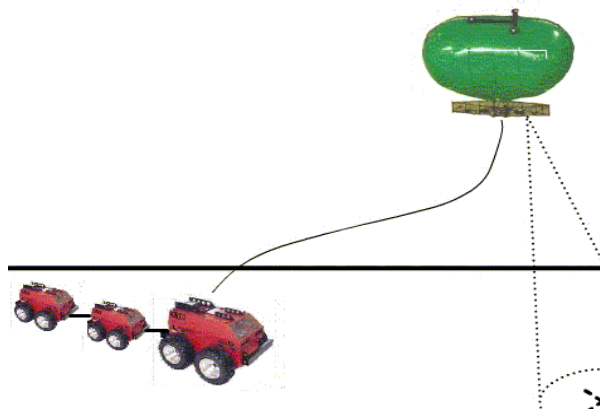
**Reactive Model-based Programming**

# Objective

Develop model-based embedded programming languages that think from commonsense models in order to robustly estimate, plan, schedule, command, monitor, diagnose and repair collections of robotic explorers.

- Reactive Model-based Programming Language
- Titan Model-based Executive

## DEMONSTRATION:



Mars 09 Mobile Science Lab



Spheres on ISS (DARPA Funded)

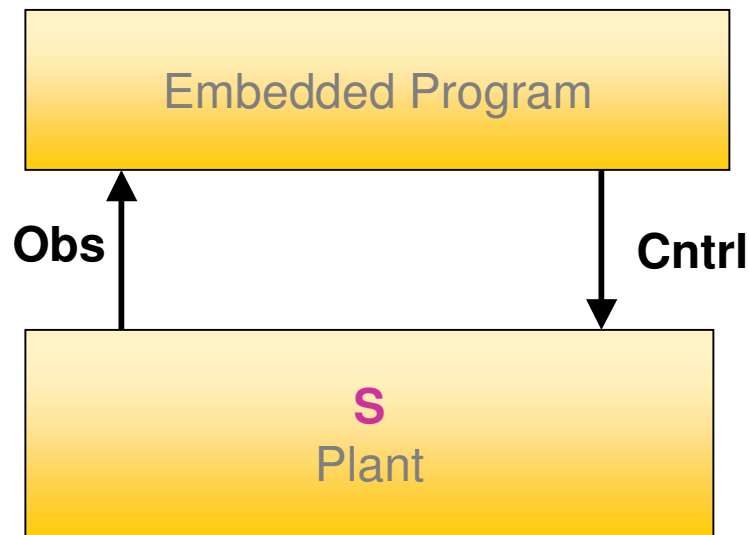
- Robust Station keeping (SIM)
- Robust Docking (MSR)



# At the Engineering level, Model-based Programs Interact Directly with State

Embedded programs interact with plant sensors and actuators:

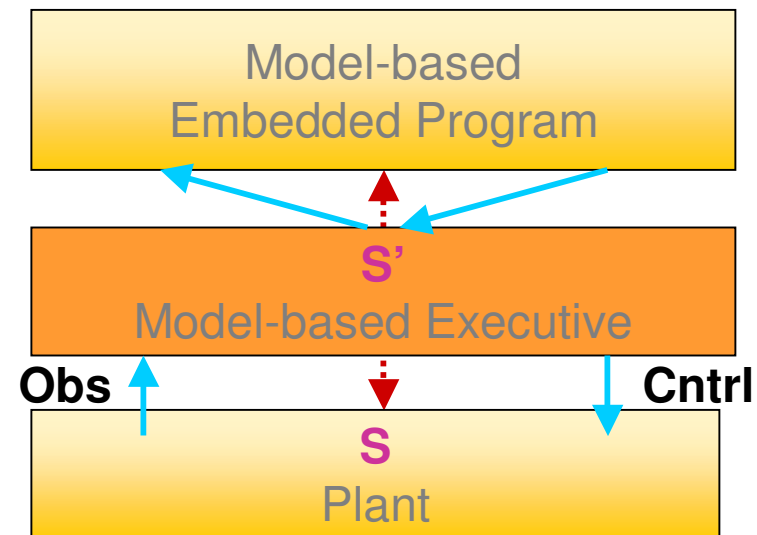
- Read sensors
- Set actuators



Programmers must map between states and sensors/actuators.

Model-based programs interact with plant state:

- Read state
- Write state



Model-based executives map automatically between states and sensors/actuators.

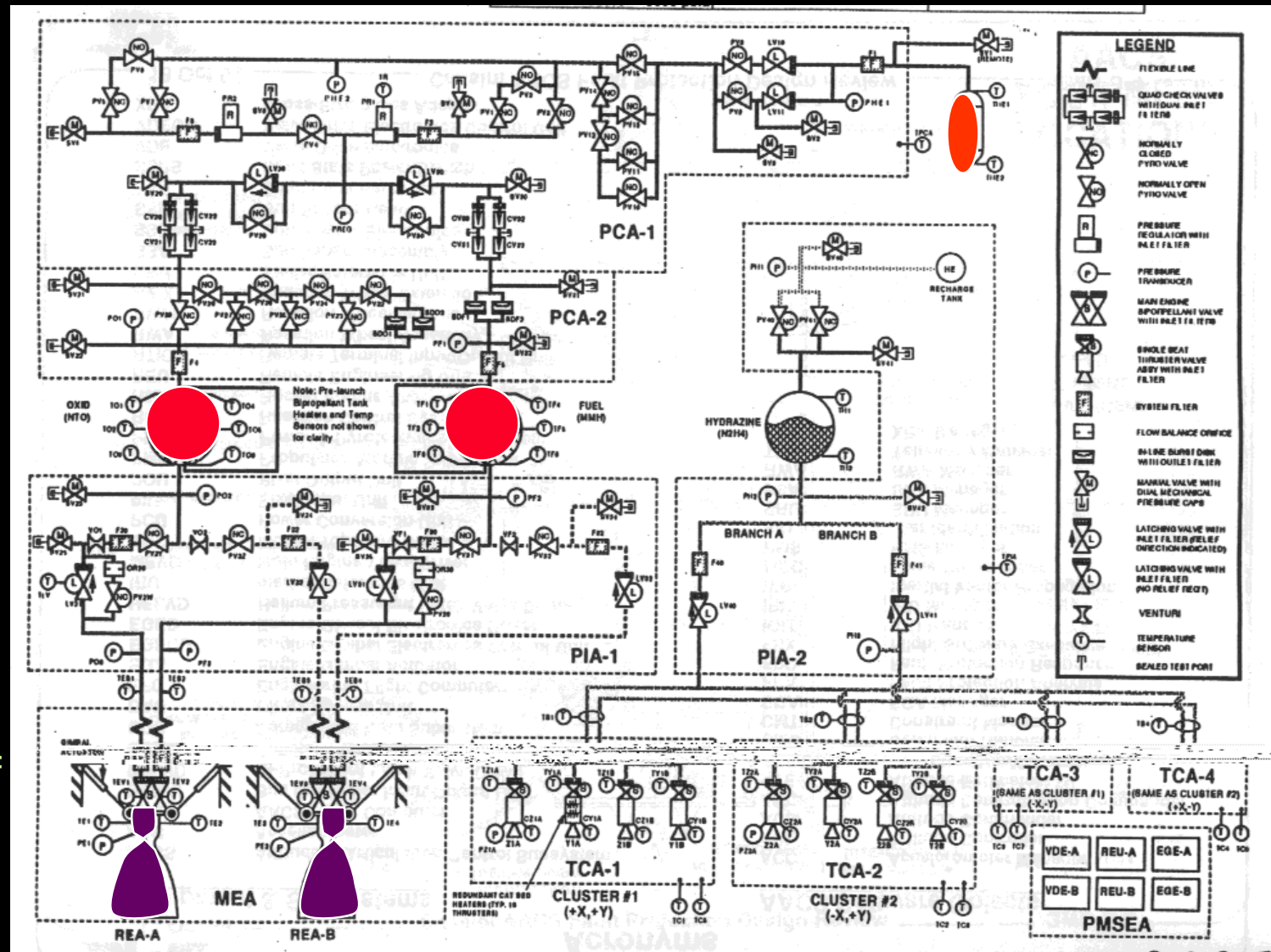
# Model-based Executives should automate **ALL** reasoning about system interactions.

Engineering level:

- Command confirmation
- Diagnosis
- Commanding
- Configuration
- Repair

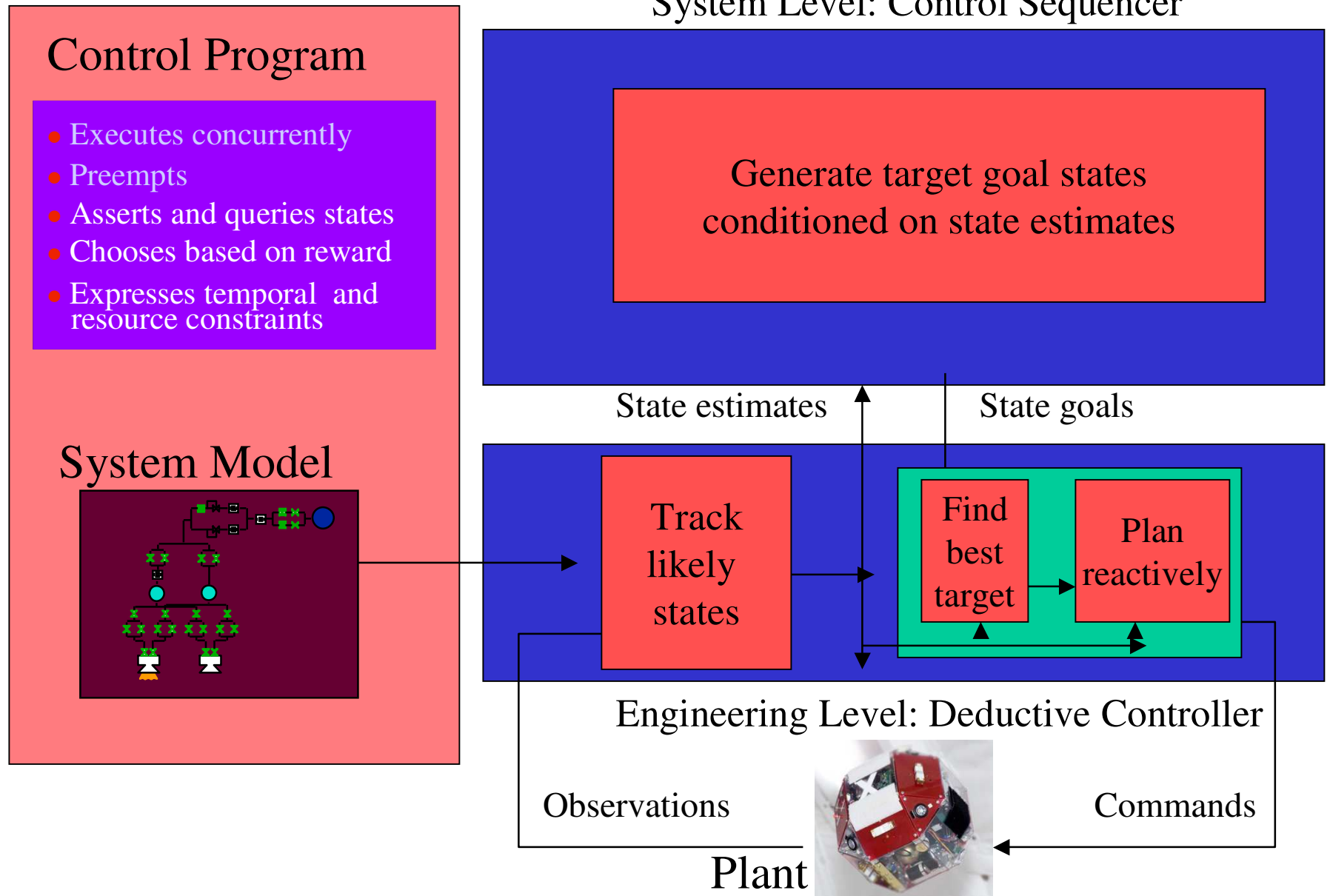
System level:

- Generation of contingencies.
- Scheduling



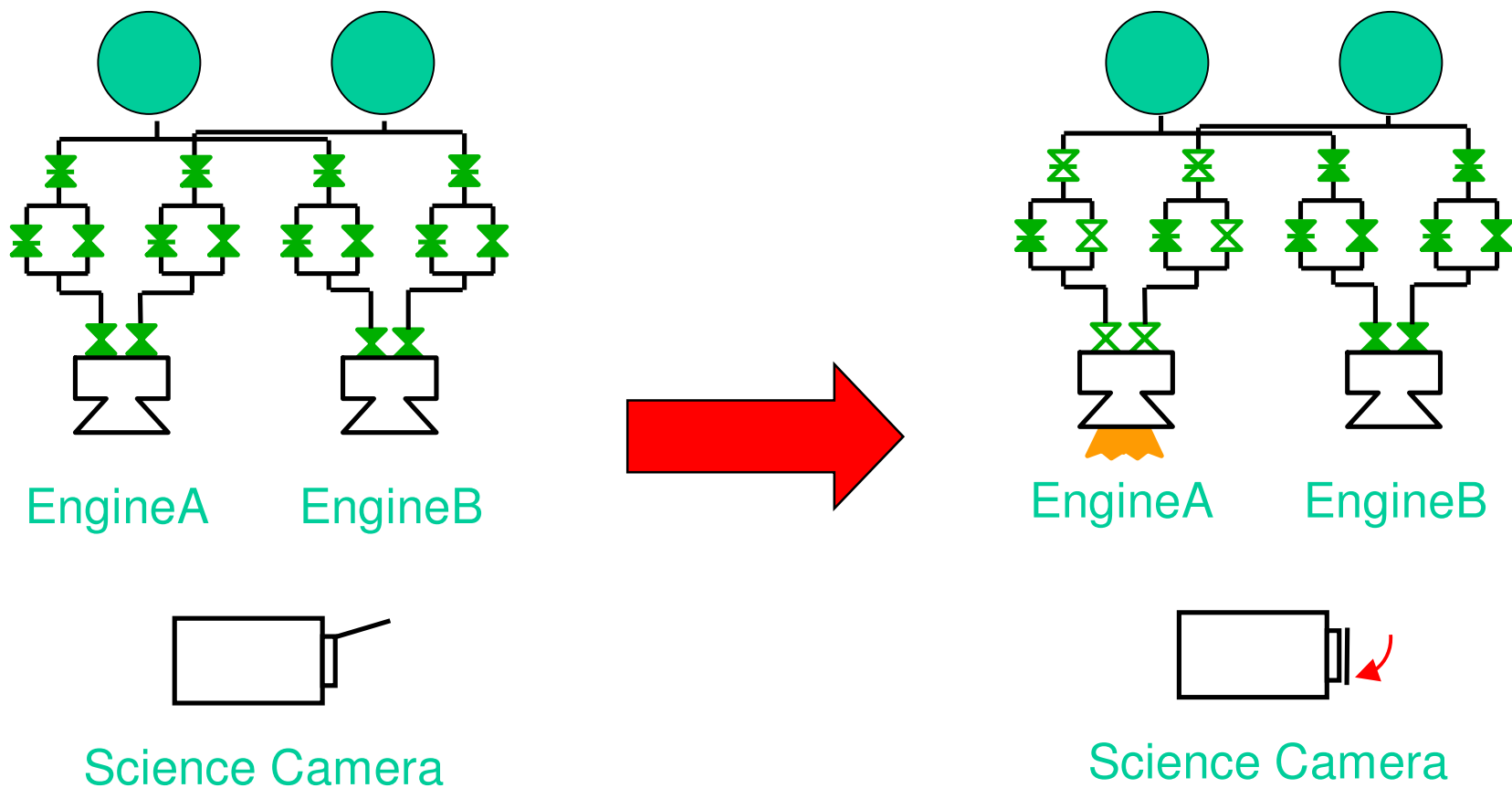
# RMPL Model-based Program

# Titan Model-based Executive



# Orbital Insertion Example

Turn camera off and engine on



Control program specifies **state** trajectories:

- fires one of two engines
- sets both engines to 'standby'
- prior to firing engine, camera must be turned off to avoid plume contamination
- in case of primary engine failure, fire backup engine instead

OrbitInsert()::

```
(do-watching ((EngineA = Firing) OR
               (EngineB = Firing))

  (parallel
    (EngineA = Standby)
    (EngineB = Standby)
    (Camera = Off)
    (do-watching (EngineA = Failed)
      (when-donext ( (EngineA = Standby) AND
                    (Camera = Off) )
        (EngineA = Firing)))
    (when-donext ( (EngineA = Failed) AND
                  (EngineB = Standby) AND
                  (Camera = Off) )
      (EngineB = Firing))))
```



# Hidden State

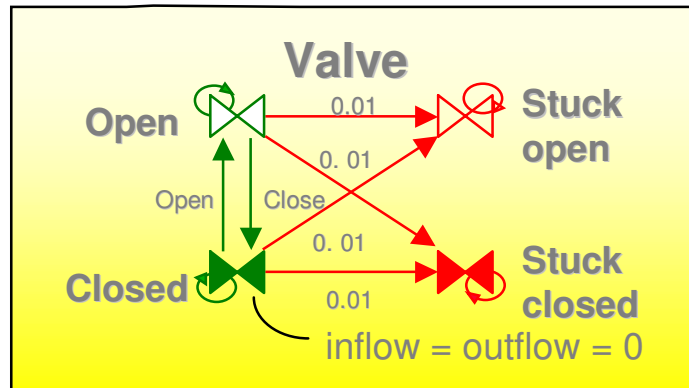
- States like (*EngineA = Standby*) are not DIRECTLY observable or controllable...

Given observations...	( <i>thrust = zero</i> ) AND ( <i>power_in = nominal</i> )
and command history...	last command issued = “standby-cmd”
executive infers “hidden state”	⇒ ( <i>EngineA = Standby</i> )
Given state goals executive infers “commands”	[ <i>Turn on DriverA</i> ]; [ <i>Open ValveA</i> ]

- Thinking in terms of “hidden states” abstracts away complexity of robustly observing and controlling state.
- Model-based executive raises assurance of software by correctly inferring and controlling states.

# Synthesize Actions from Models of Complex Behavior

Intended  
Behavior  
of System

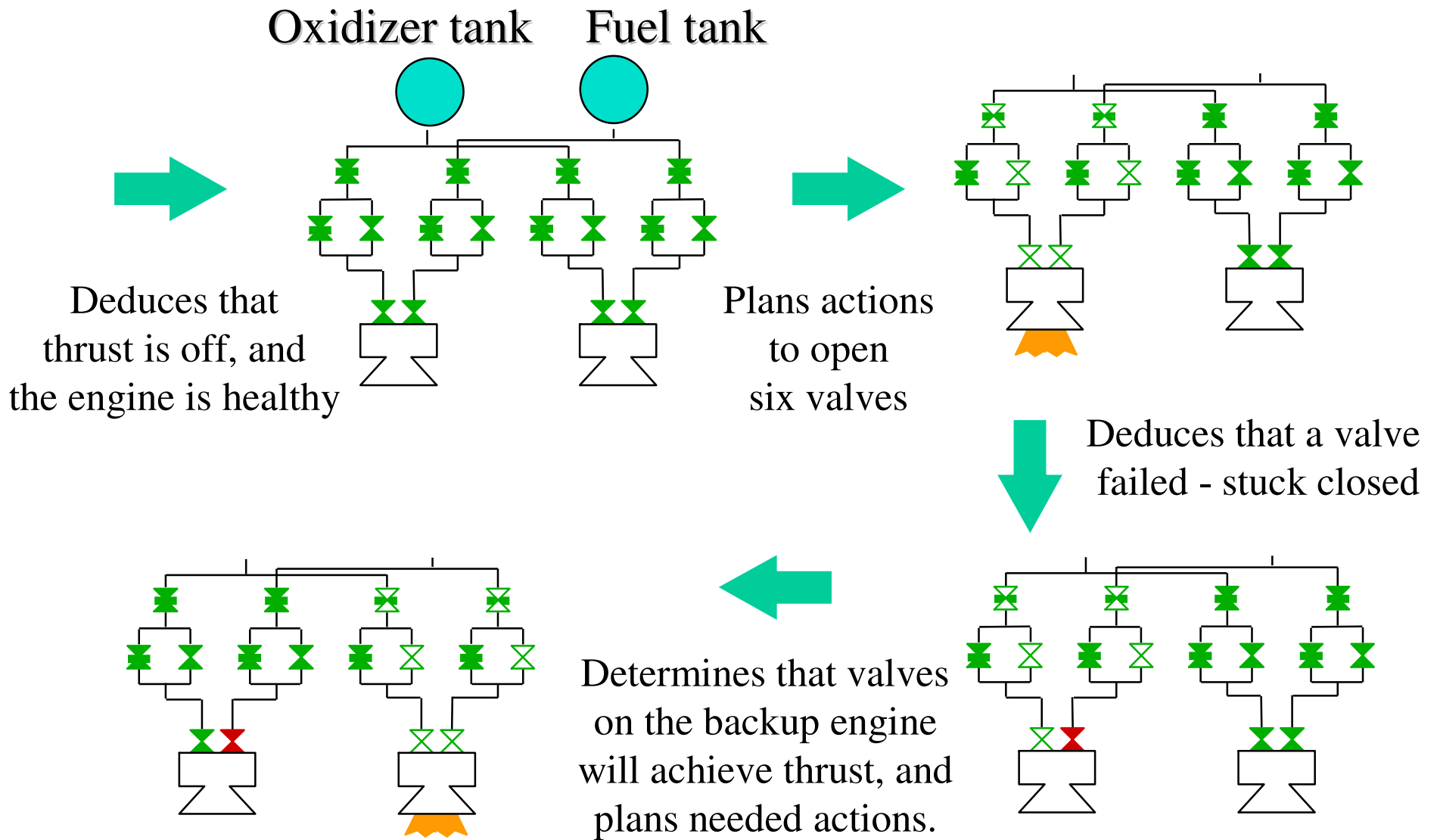


Possible  
Behaviors  
of Components

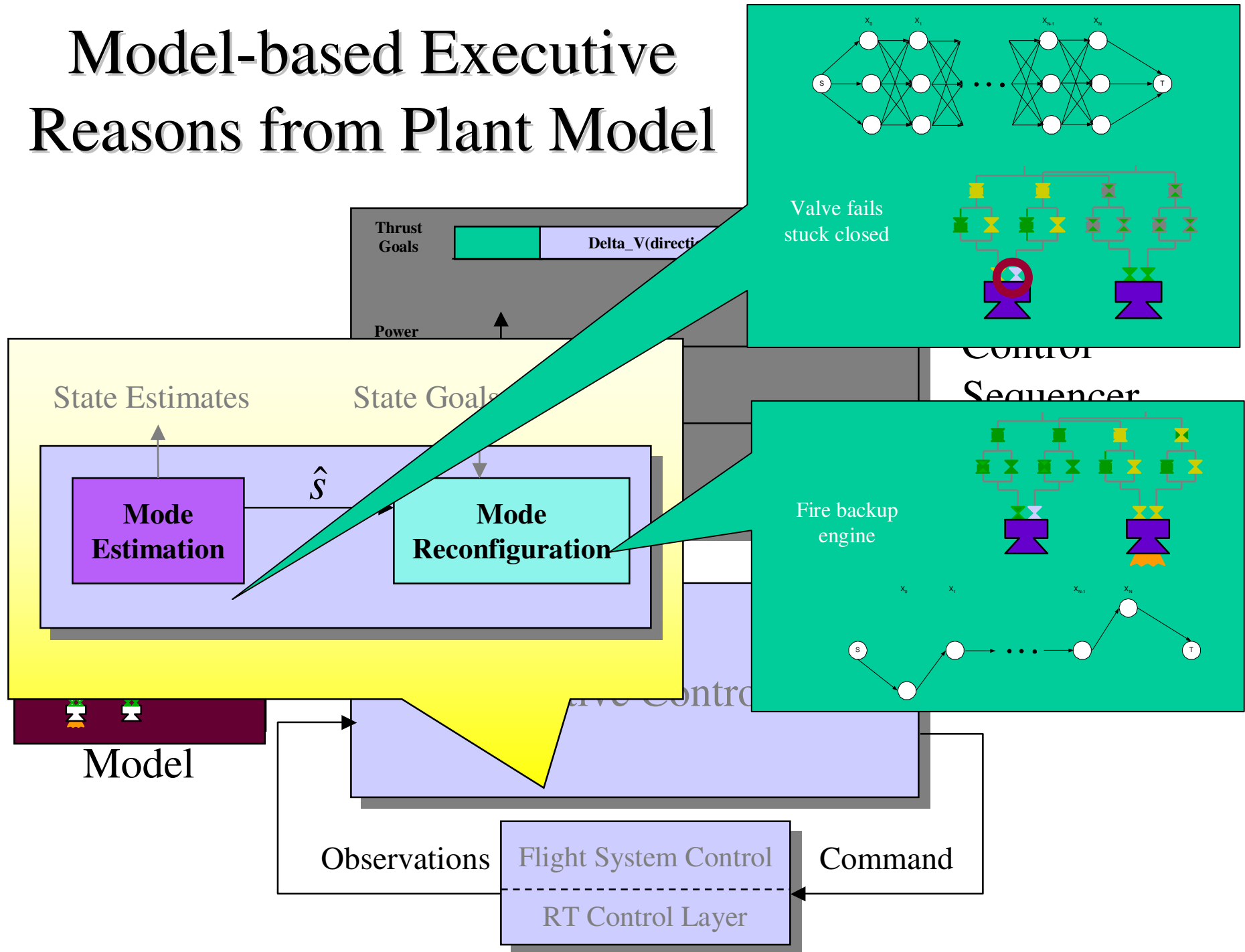
## Probabilistic Hierarchical Constraint Automata:

- Complex, discrete and qualitative behaviors
  - modeled through **concurrency**, **hierarchy** and **non-determinism**.
- Anomalies and uncertainty
  - modeled by **probabilistic transitions**
- Physical interactions
  - modeled by **discrete** and **continuous constraints**
- Timing
  - modeled by **simple temporal networks**

Example: The model-based program sets the state to thrusting, and the deductive controller . . . .



# Model-based Executive Reasons from Plant Model



## Model-based Programming:

- B. C. Williams and M. Ingham, "Model-based Programming: Controlling Embedded Systems by Reasoning about Hidden State," *to appear International Conference on Constraint Programming, September 2002.*

## MBP & Titan Executive 1.0:

- B. C. Williams, M. Ingham, S. Chung and P. Elliott, "Model-based Programming of Intelligent Embedded Systems and Robotic Explorers," *to appear Special Issue on Embedded Software, IEEE Proceedings.*



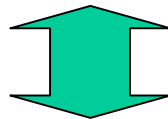
# Results: Analysis of Livingstone Deductive Algorithms

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## Issues:

- Would not explore complete diagnosis space.
- Would not maintain proper ranking of diagnoses in terms of posterior probability.
- Would not rule out all inconsistent diagnoses.



## OPSAT:

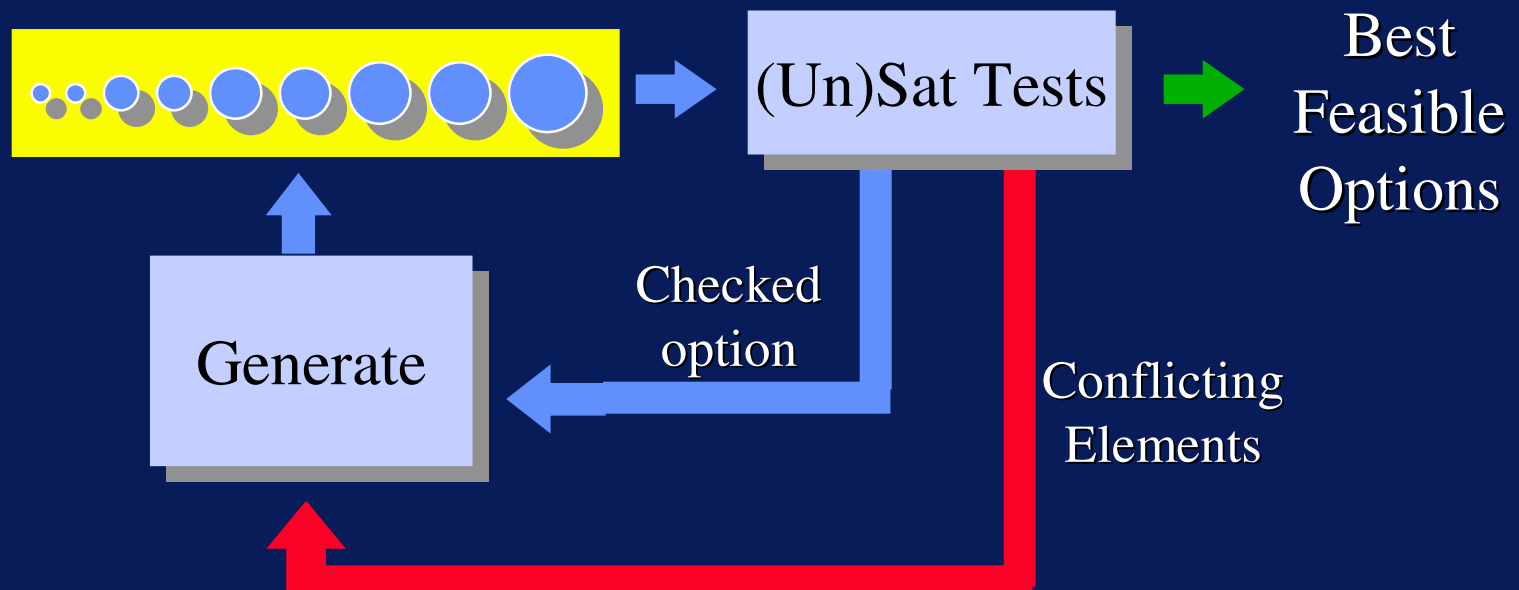
- Extract Deductive core for solving Optimal Constraint Satisfaction problems.
- Extend to achieve optimality, completeness, and correctness.
- Empirically validate on randomized algorithms and extend

Generate Best Options:

- 

Test Against Constraints:

- 

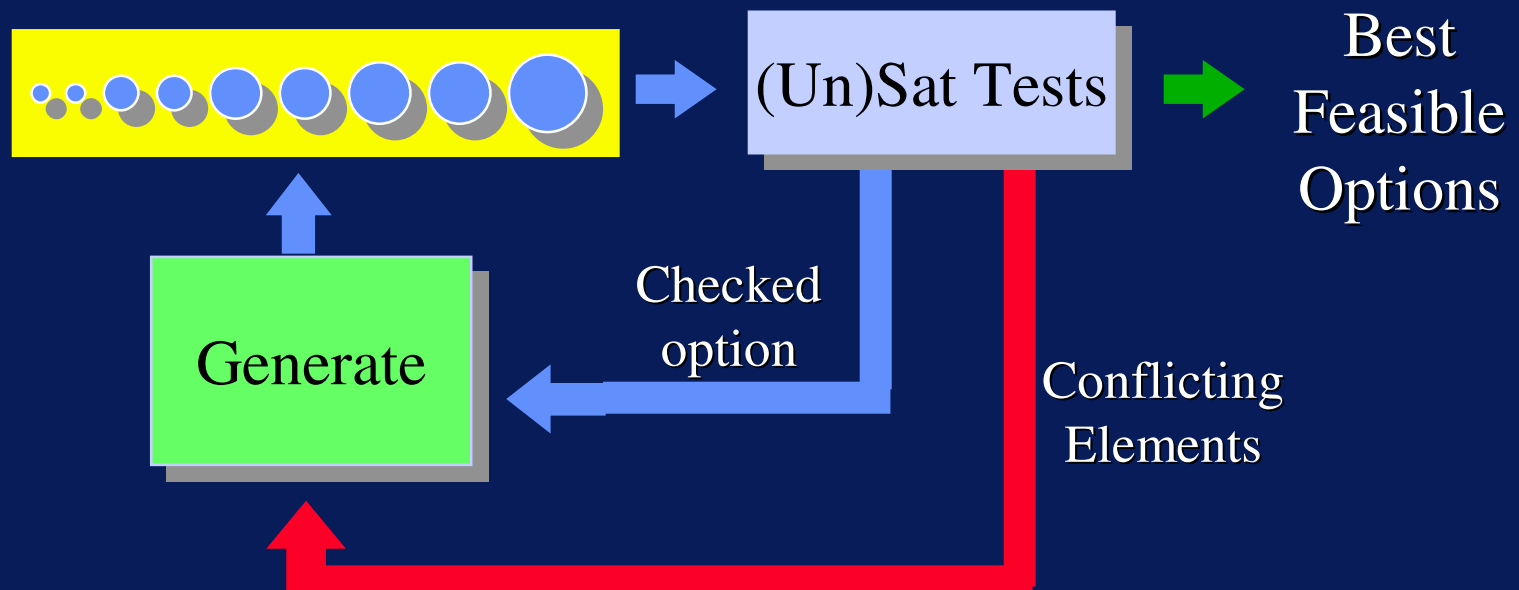


## Generate Best Options:

- Conflicts generalize test to leap over leading infeasible options

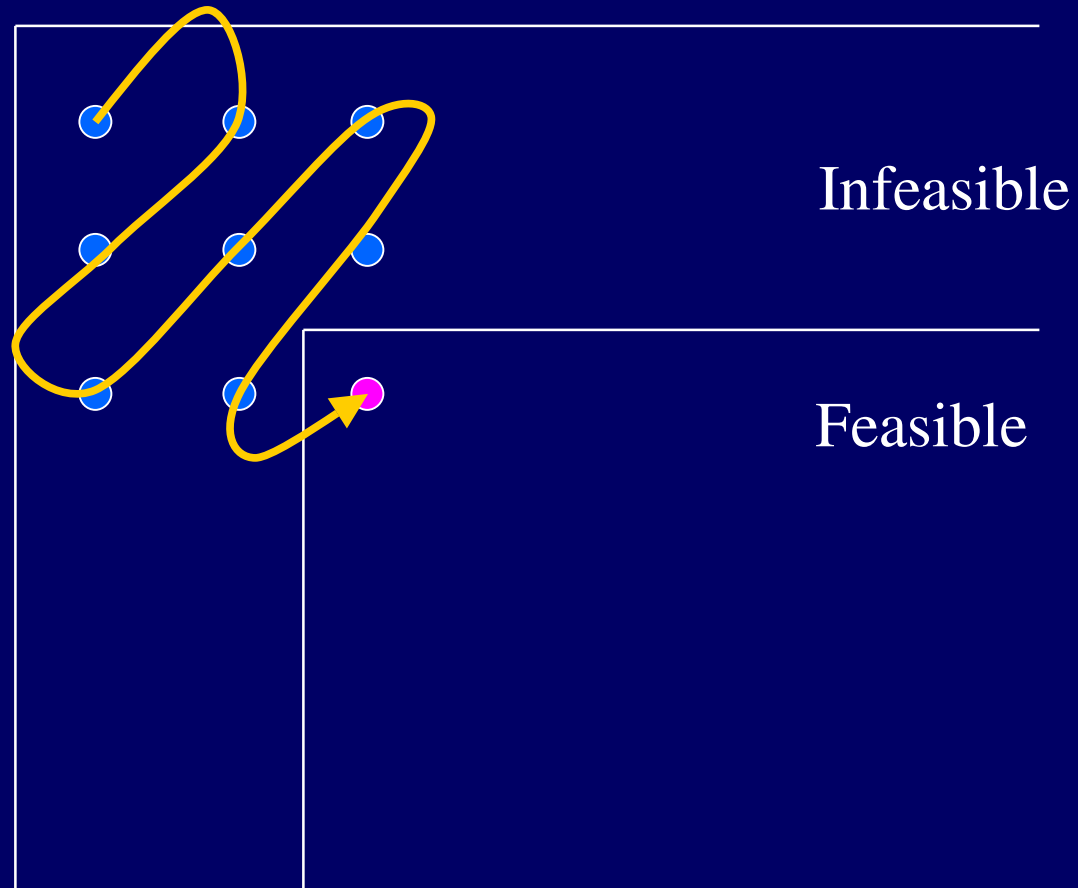
## Test Against Constraints:

- Directed towards satisfying most constraints



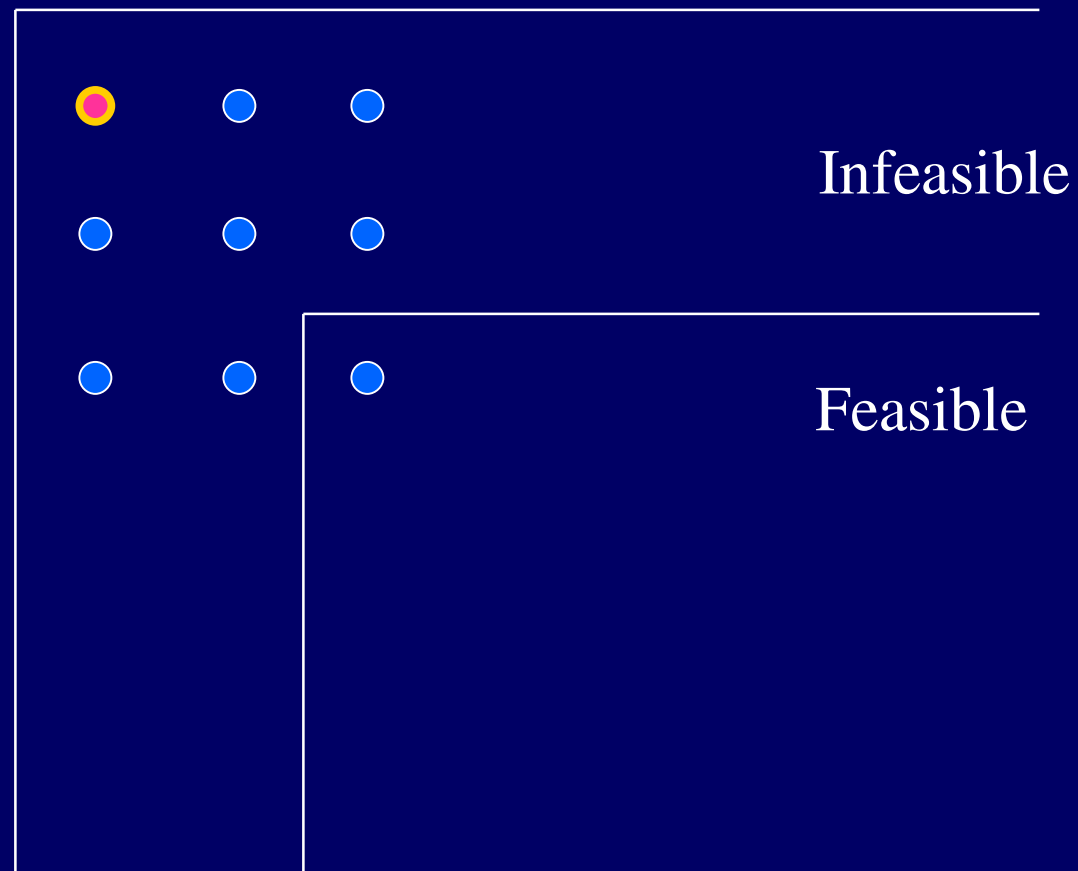


Increasing  
Cost



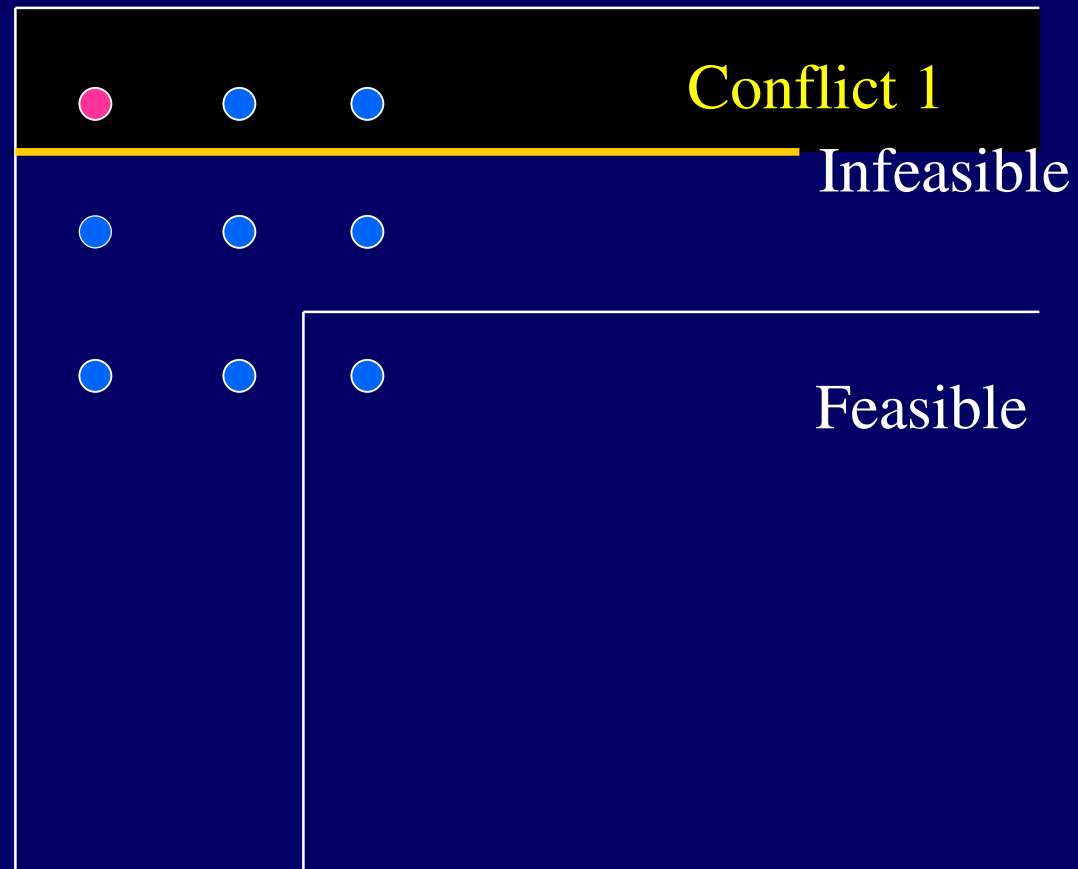
# Conflict-directed A\*

Increasing  
Cost



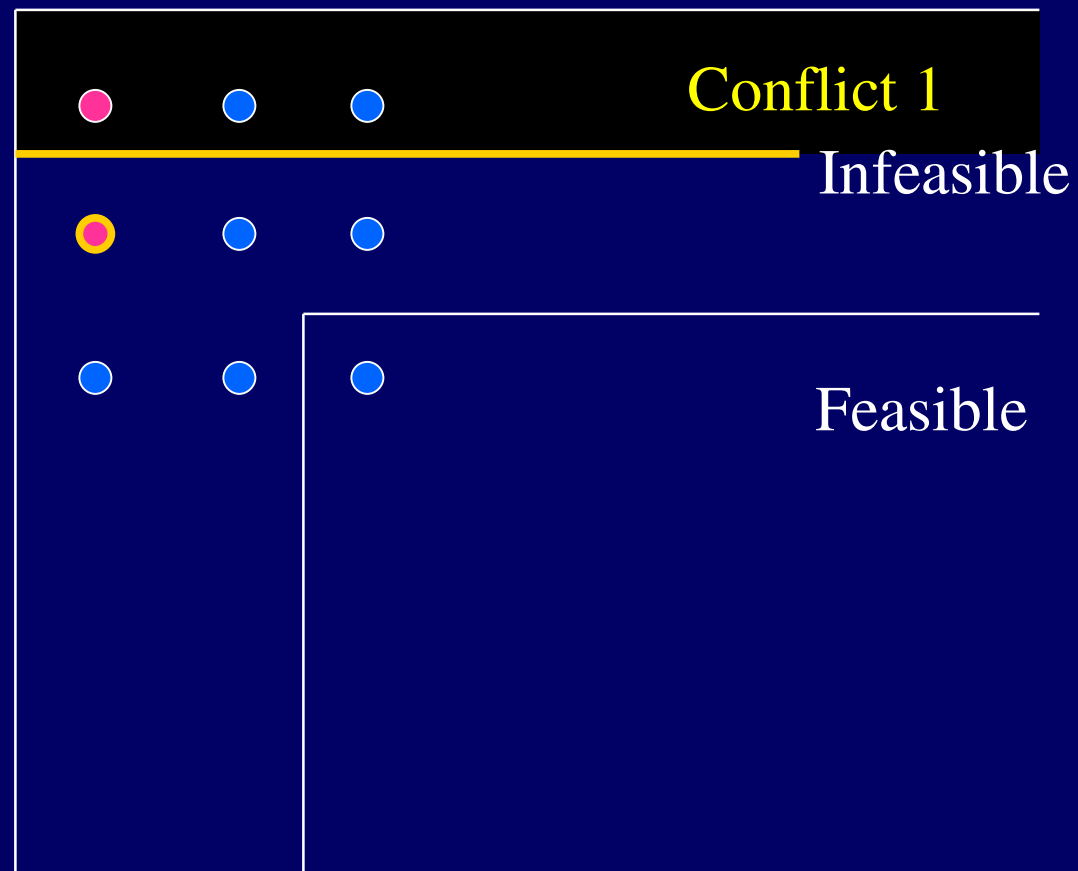
# Conflict-directed A\*

Increasing  
Cost



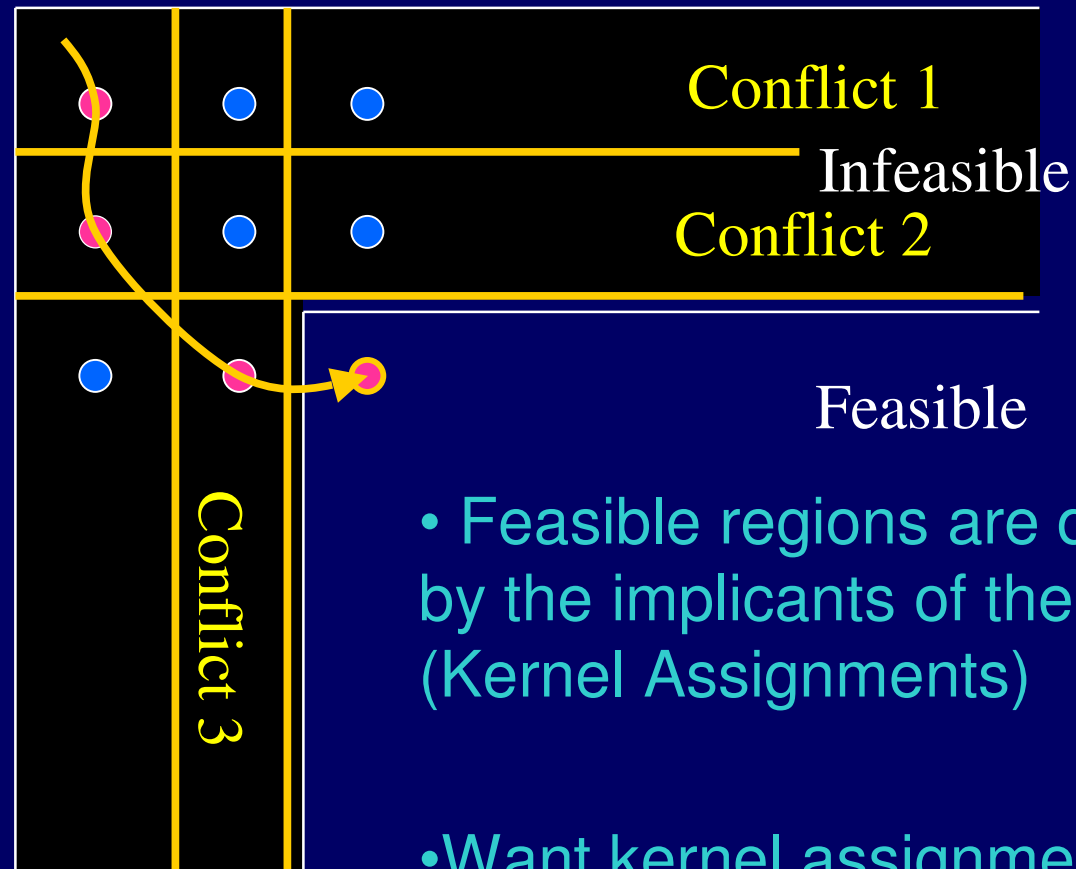
# Conflict-directed A\*

Increasing  
Cost



# Conflict-directed A\*

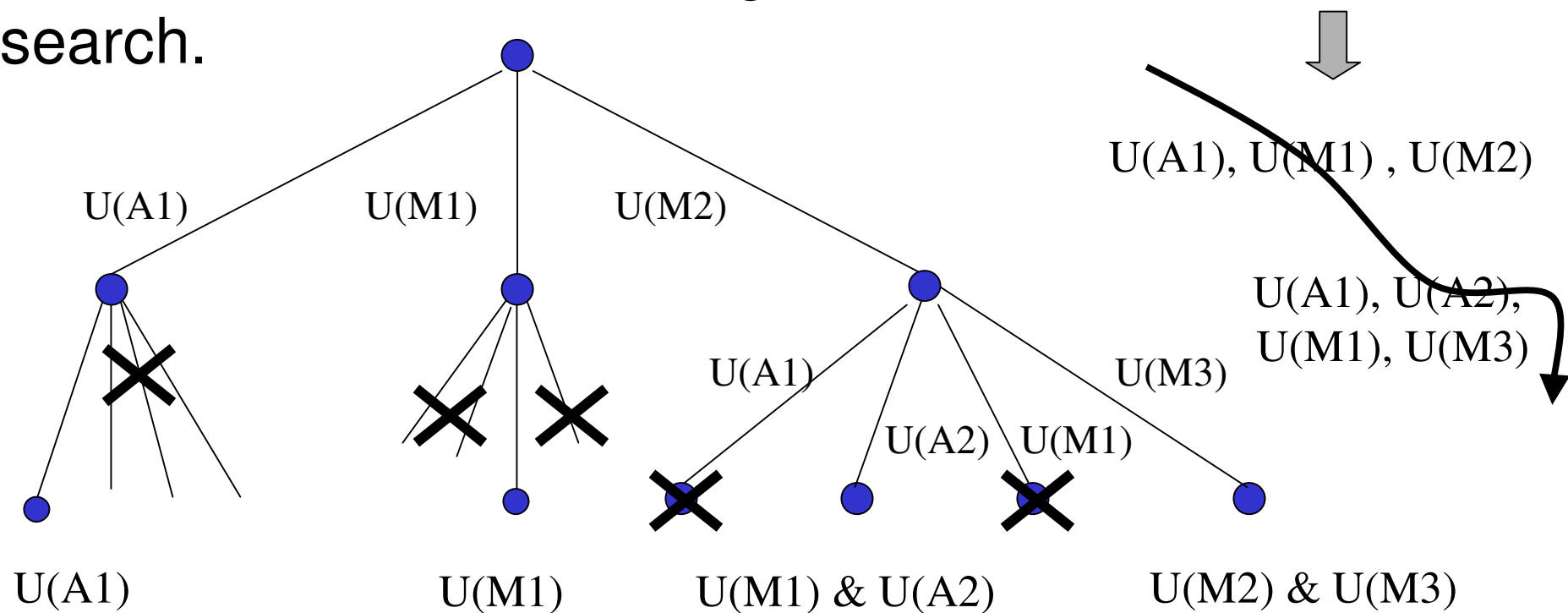
Increasing  
Cost



- Feasible regions are described by the implicants of the conflicts (Kernel Assignments)

- Want kernel assignment containing the best cost state.

- Kernel assignments are generated from conflicts by minimal set covering.
- View minimal set covering as tree search.

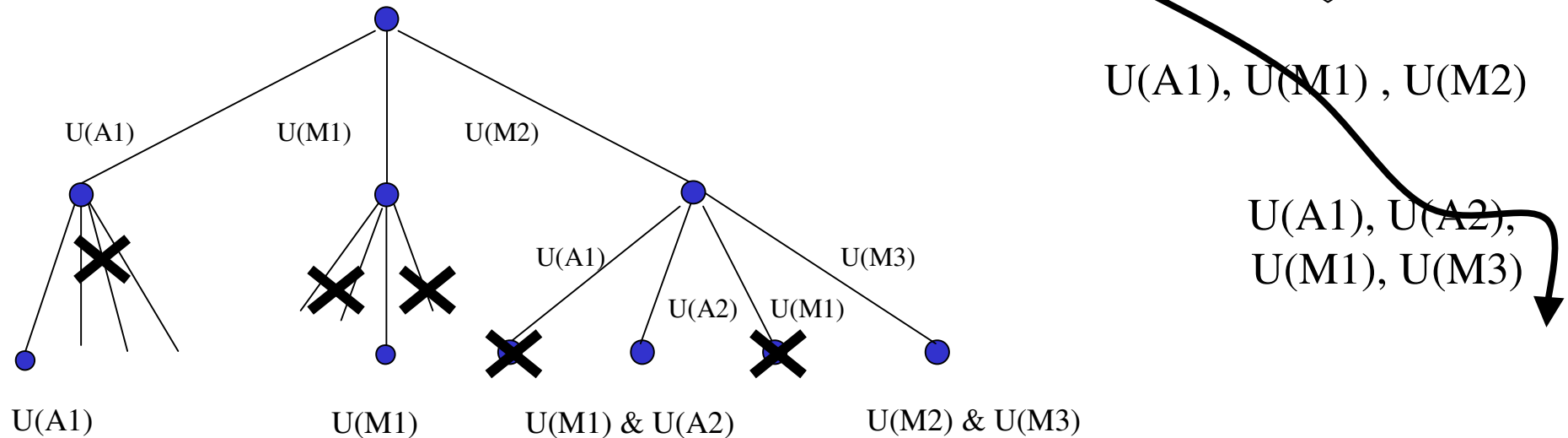


Conflict-directed A\*:

- To find best kernel, expand tree in best first order, exploiting preferential independence, preserve systematicity
- Explore subspace of kernel in best first order.
- Test with Incremental Sat algorithm (DPLL + TMS)

# How do we unify Generate and Test phases?

- Treat all clauses as conflicts.
- Direct towards covering clauses.



## Clause-directed A\*:

- Search in best first order, exploiting preferential independence.
  - All else equal, direct towards assignments covering most clauses.
  - Perform incremental unit propagation after each assignment.
- ➔ Produces best cost **prime implicants**.



# Recent Publications: Optimal CSPs & OpSat

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Using conflicts to optimally direct the selection of decision variables.

- Williams, B.C. and R. Ragno, “Conflict-directed A\* and its Role in Model-based Embedded Systems,” *to appear* Special Issue on Theory and Applications of Satisfiability Testing, Journal of Discrete Applied Math.

Unifying Generation and SAT Testing through Clause-direction

- Ragno, R. “Clause-directed A\*,” Master’s Thesis, MIT EECS

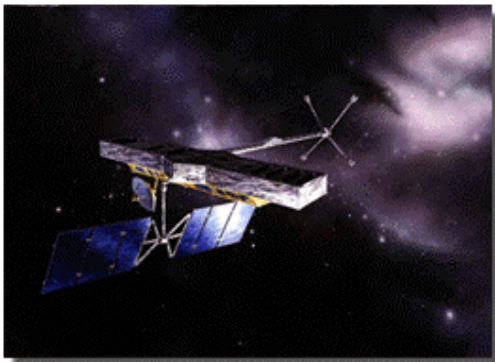




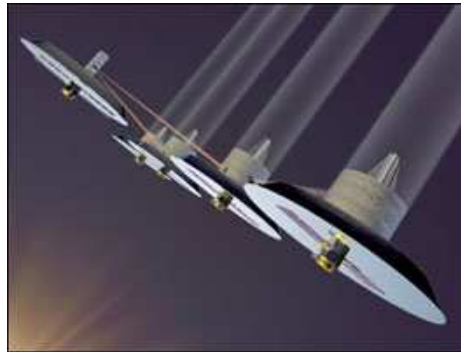
# Demonstration 1: Interferometer Testbed



Objective: Successful ground test-bed demonstration:  
1<sup>st</sup> step toward broader acceptance.



SIM



TPF

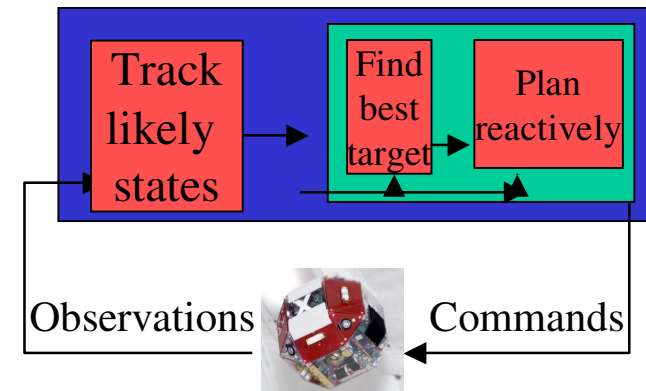
Collaborators: JPL Caltech

Publication:

- Ingham, M., B. Williams, T. Lockhart, A. Oyake, M. Clark, A. Aljabri, "Autonomous Sequencing and Model-based Fault Protection for Space Interferometry," International Symposium on AI and Robotics in Space, June 2001.

Terminated: Spring 01

Deductive Controller  
(lisp Livingstone)



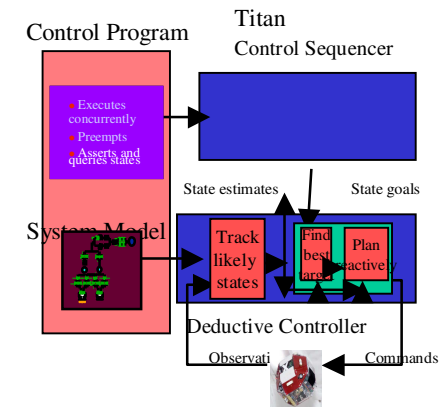
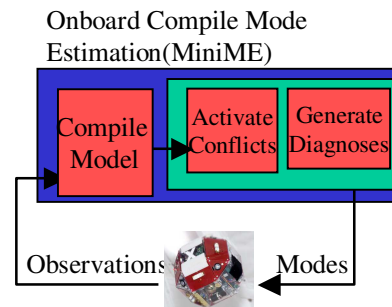
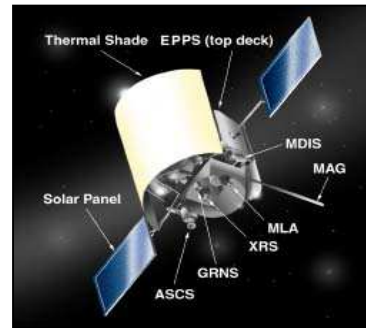


# Demonstration 2 &3: Messenger On & Off Board



Objective: Demonstrate approach to Mode Estimation that is palatable to conservative missions.

Messenger  
Mission to  
Mercury

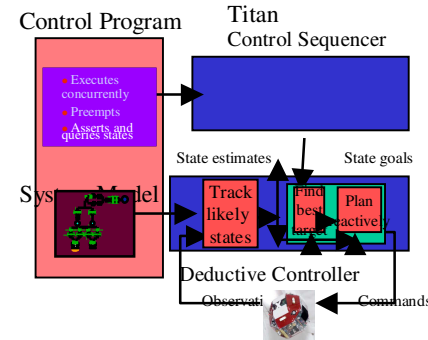


Collaborators: JHU APL Dave Watson, Mike Pekala...

Publication: Van Eepoel, J., B. Williams, S. Chung, "Improving Model-based Mode Estimation Through Offline Compiling," International Symposium on AI and Robotics in Space, June 2001.

Status:

- Funding delayed to 8<sup>th</sup> month, FY 01,
- 1 month for Minime to reach Messenger PDR-> too late.
- Shifted to Titan ground station.
- Funding terminated after 4 months, still an excellent opportunity!



## Collaborators:

- MIT Space Systems Lab (Miller, Sedgwick, How, Fesq),
- MIT AI Lab (Shrobe, Ladagga, Sullivan, Roberston),
- JPL AIG (Chien, Rabideau, Sherwood), AFRL

## Publication:

- Chien, S., R. Sherwood, M. Burl, R. Knight, G. Rabideau, B. Engelhardt, A. Davies, P. Zetocha, R. Wainright, P. Klupar, P. Cappelaere, D. Surka, B.C. Williams, R. Greeley, V. Baker and J. Doan, "The Techsat-21 Autonomous Sciencecraft Constellation," Int. Symp. on AI, Robotics and Automation in Space, St-Hubert, Canada, June 2001.

Status:

- Started FY 99 under AFRL funding, augmented by DARPA Mobies
- Replaced by L2, January, 2002.



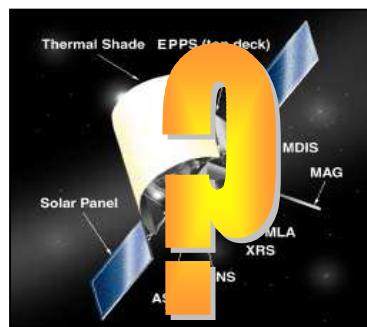
# Demonstration 5 & 6: ST –7 Concept Study

## Model-based Programming at Engineering & System Levels



Objective: Demonstrate Model-based Programming on board at Engineering and Systems Levels, operate full mission

NASA ST7  
Mission  
Phase A



Collaborators:

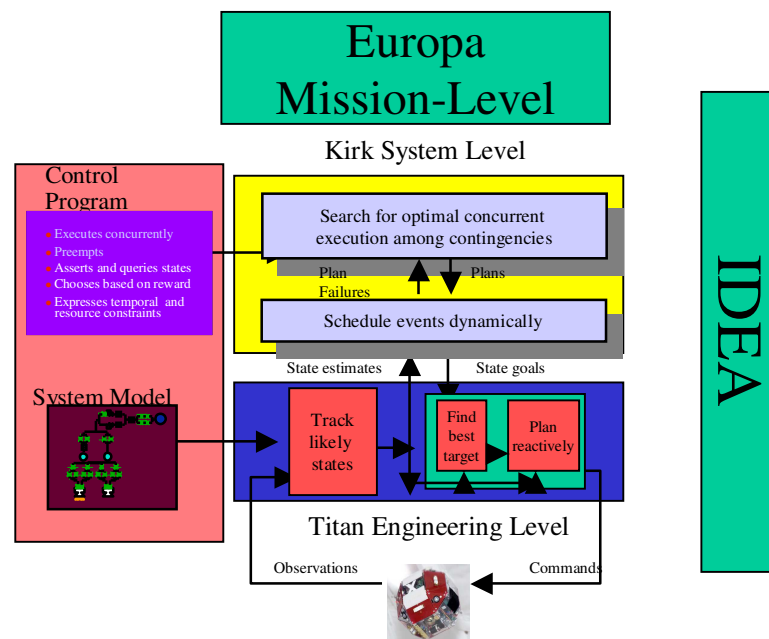
- JPL (Beam Group) AIG (Barret)
- JHU APL (Watson, Pekala)
- NASA Ames (Muscettola, Morris)

Publication:

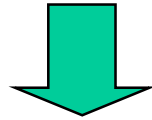
- Fesq, L., et al. “Model-based Programming for Robotic Spacecraft” *to appear, World Space Congress, 2002.*

Status:

- Completed integrated demo of System level (Kirk) and Eng. Level (Titan)
- Awaiting Mission level autonomy and IDEA for full integrated demo.



# Directions: Spheres on ISS

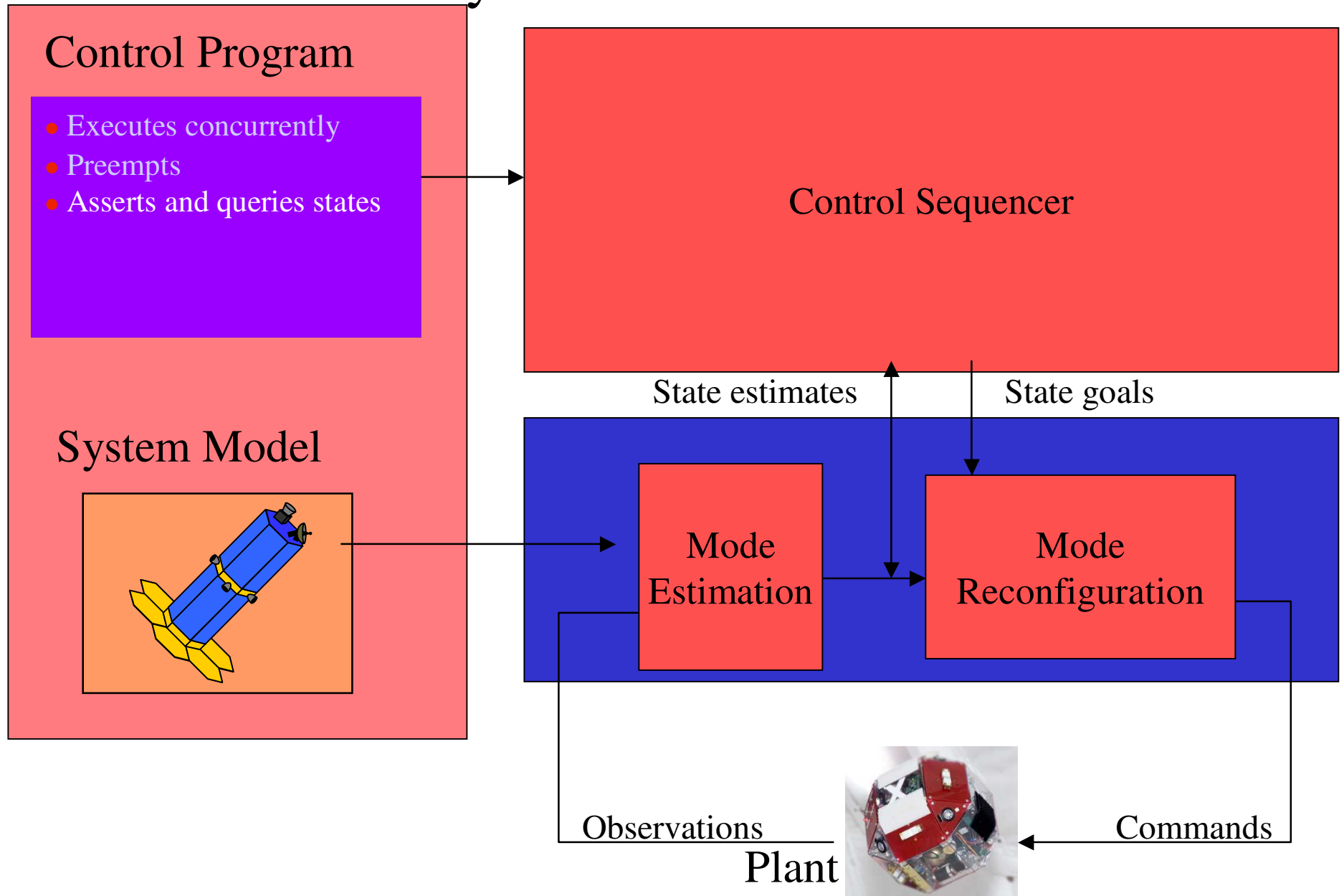


- Working to demonstrate Titan in flight on docking maneuvers for MIT Sphere's Spacecraft within Intl. Space Station.
- Titan must manage mission in light of failures.



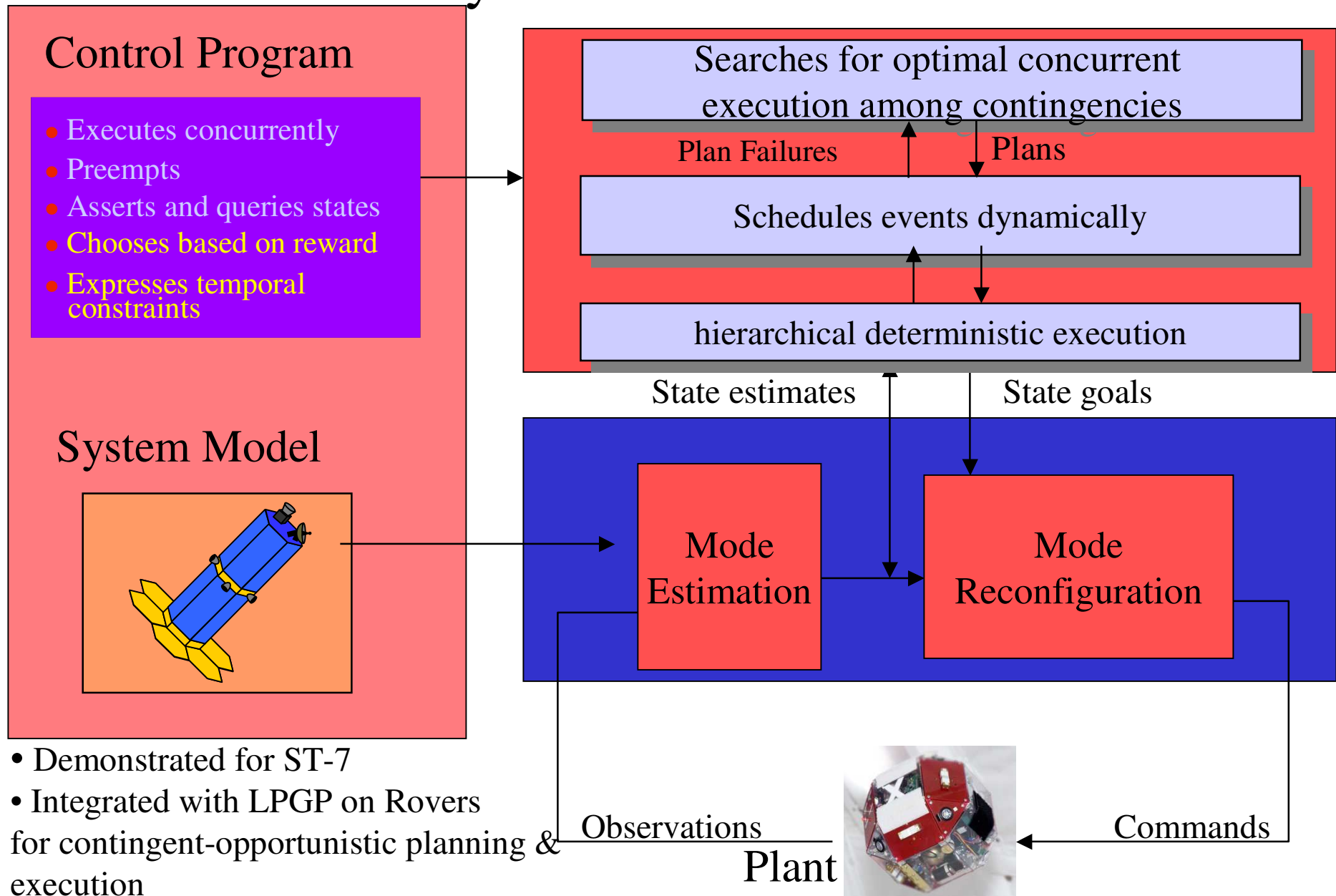
Funded by DARPA Orbital Express

# Directions: Expanding Model-based Programming to the System-level: Titan + Kirk





# Directions: Expanding Model-based Programming to the System-level: Titan + Kirk



# Heterogeneous Cooperative Robotics



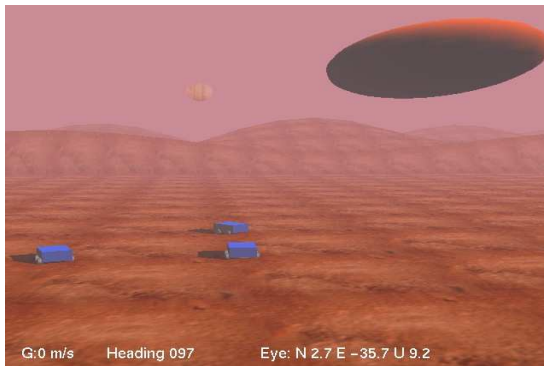
- Orbiter
- Tethered Blimp
- Mobile Lander
- Scout Rovers
- Sensor Network



# Indoor Testbed



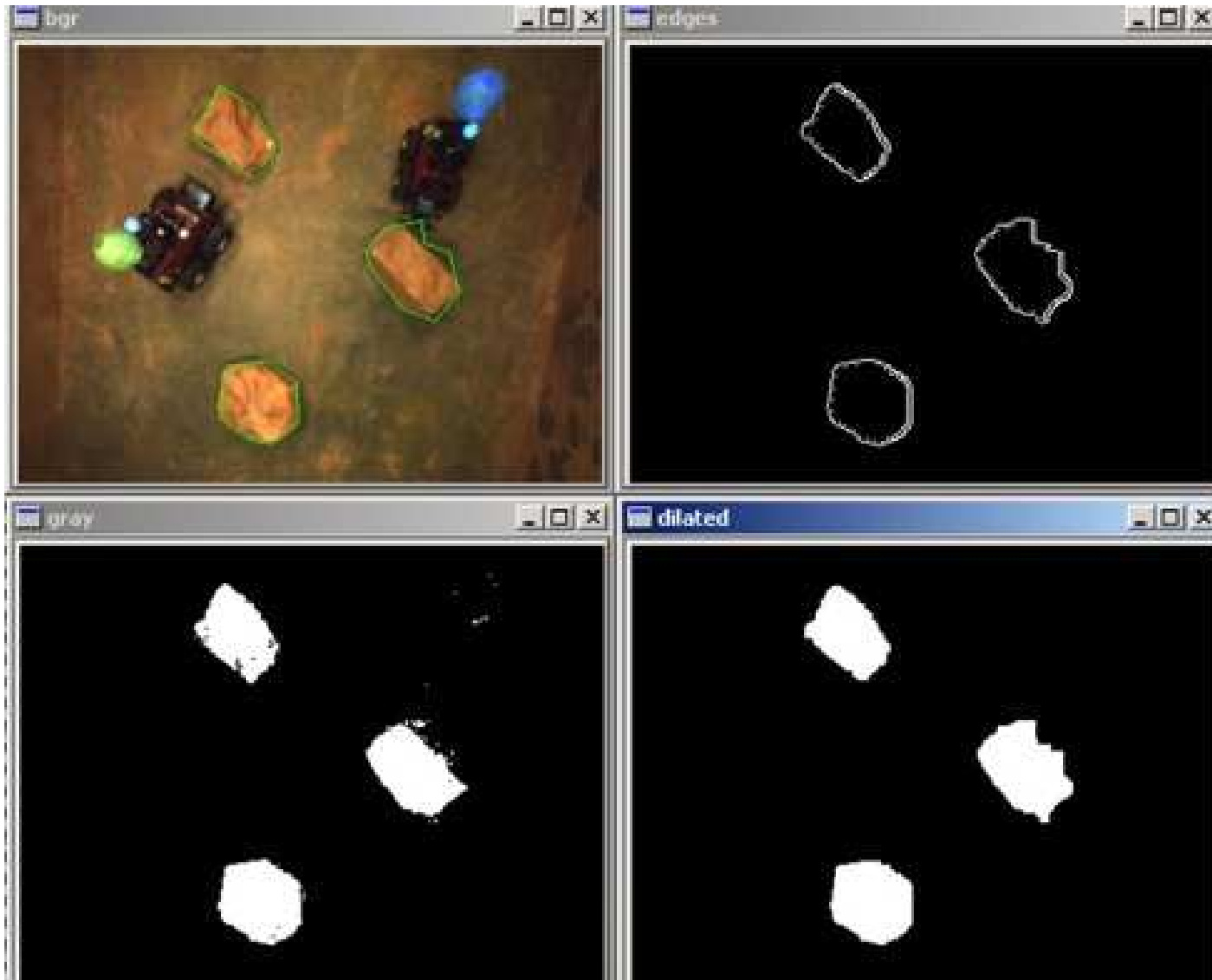
- One ceiling mounted stereo camera “the blimp”
- 3 ATRV jr.
- 1 ATRV
- Rover Sensors
  - Stereo camera head
  - Sonar array
  - Laser range scanner
  - DGPS
  - Wheel encoders
  - Digital compass
- Motes Sensor Networks



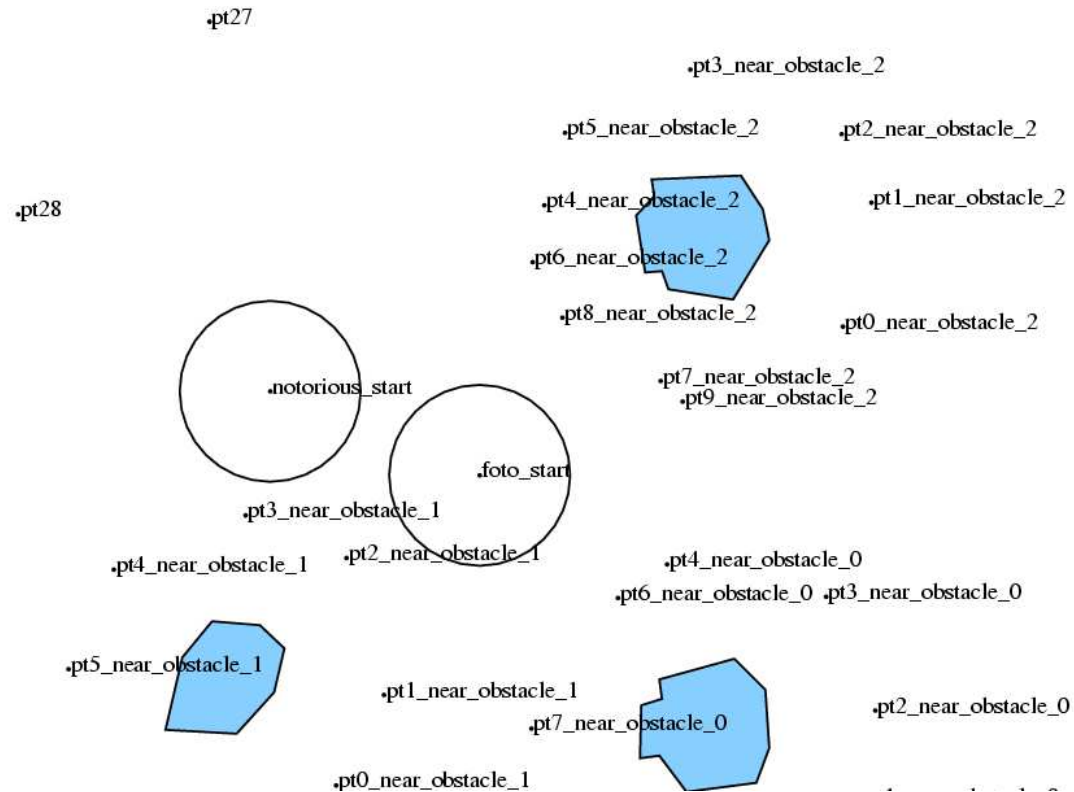
**Rover Sim**

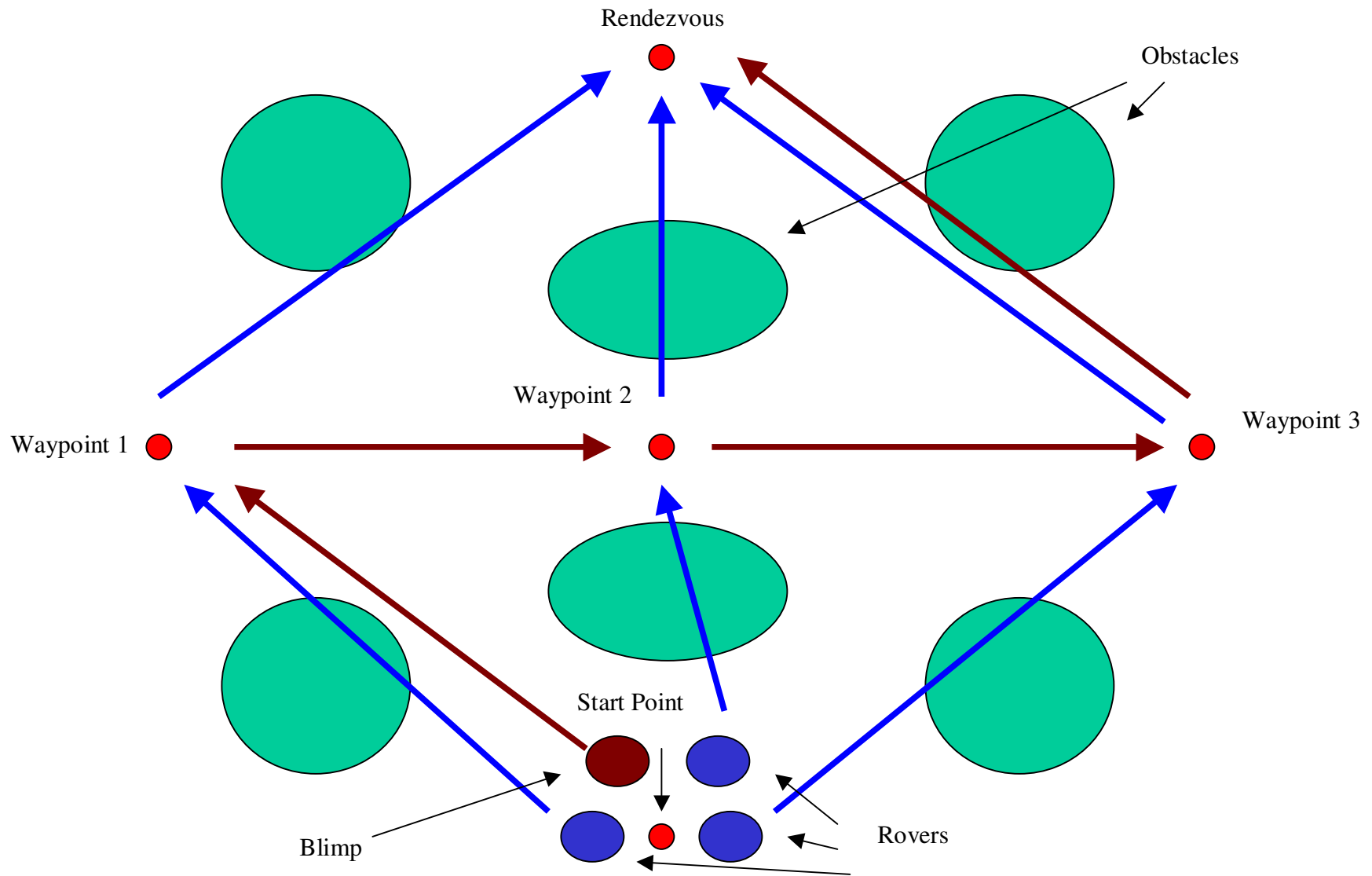


# Obstacle Detection



# Map Generation

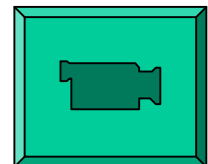
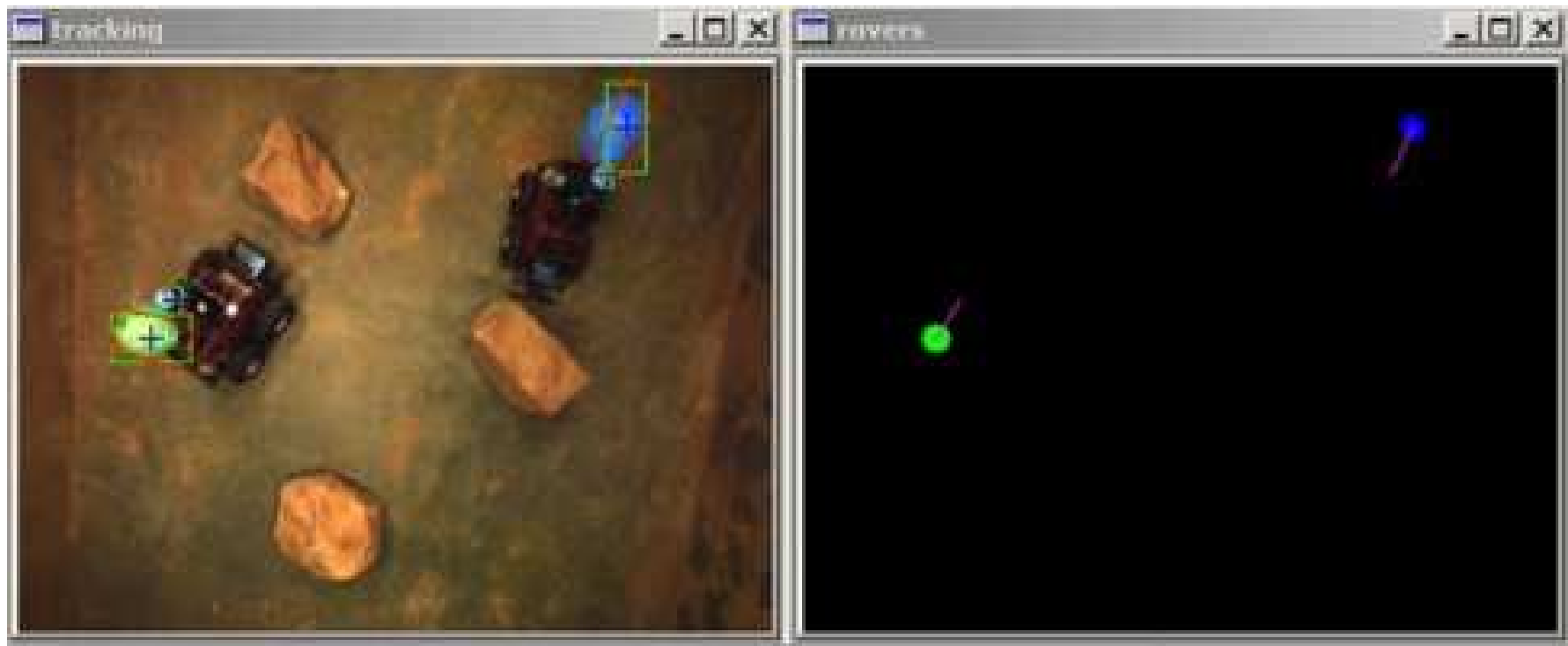




demo on sim



# Rover tracking during execution



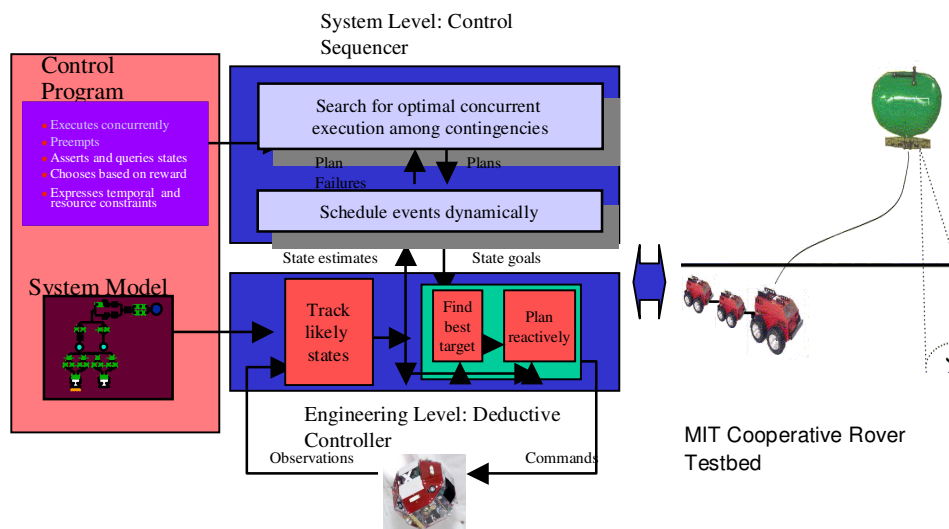


# Issues

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As a university, how can we effectively establish a path for our technology to MSL, and other missions, and how do we secure funds to support this?



## TASK OBJECTIVES:

Develop model-based embedded programming languages that think from commonsense models in order to robustly command, monitor, diagnose and repair collections of robotic explorers.

## TECHNICAL INNOVATIONS:

- RMPL language reads and writes hidden state variables as if directly observable and controllable
- Titan executive “reads” state by automatically deducing it from sensor information.
- Titan executive “sets” state by planning command sequences that move to the specified state.

**SPONSOR:** NASA Code-R (CETDP)

**DEVELOPMENT TEAM:** MIT, [APL IS]

Milestones	FY02	FY03	FY04
Develop RMPL Compiler	X		
RMPL executive	X	X	
Distributed RMPL executive		X	X
•Demonstrate on Distributed Space System Testbed(s)		X	X

## NASA RELEVANCE:

- Provides high assurance software for space missions.
- Offers robust capabilities for command execution and fault management.
- Speeds time for development and testing of flight software.
- Dramatically expands ability to robustly respond to novel situations.



# Model-based Programming as Estimating, Planning and Executing based on Hidden State

Brian C. Williams

Artificial Intelligence and Space Systems Labs

Massachusetts Institute of Technology

IS Program Review

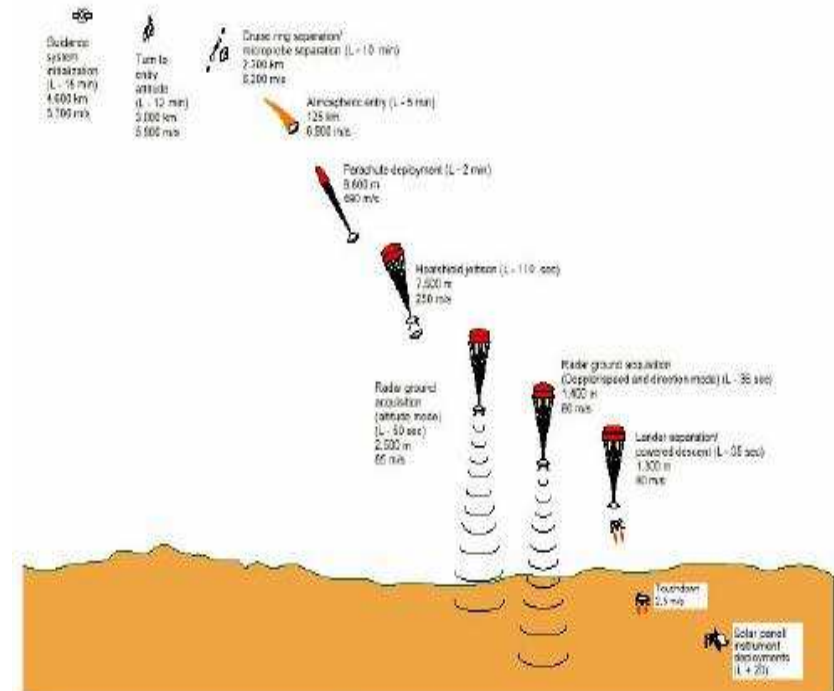
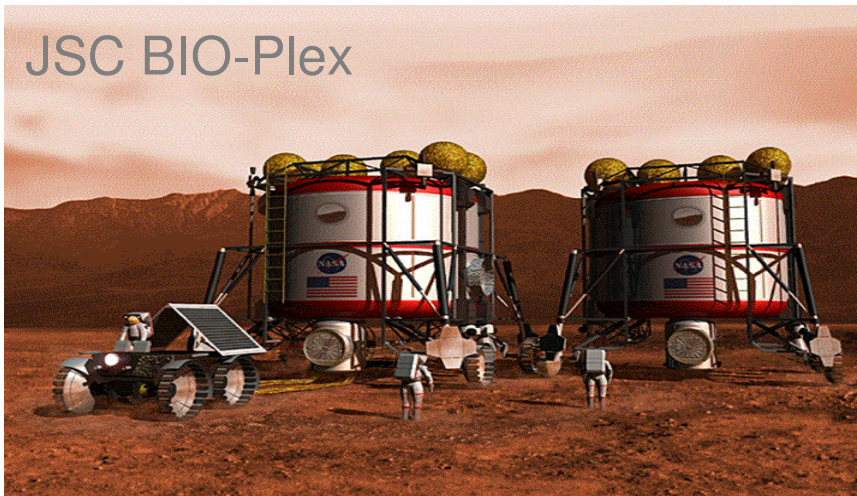
September 5<sup>th</sup>, 2002



# Objective

Create a hybrid estimation, monitoring, diagnosis and model learning capability for physical devices that exhibit complex discrete and continuous behaviors.

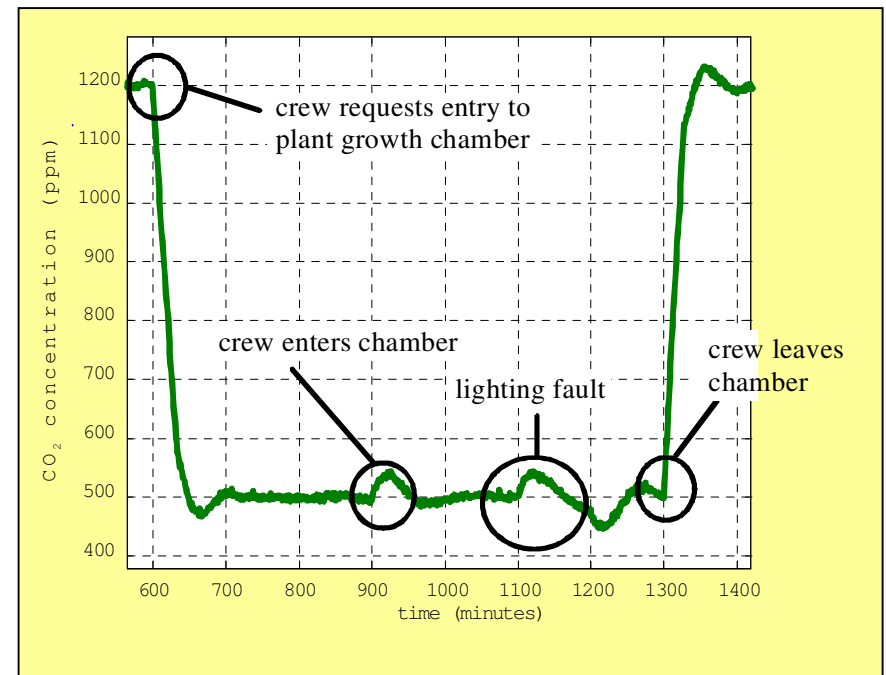
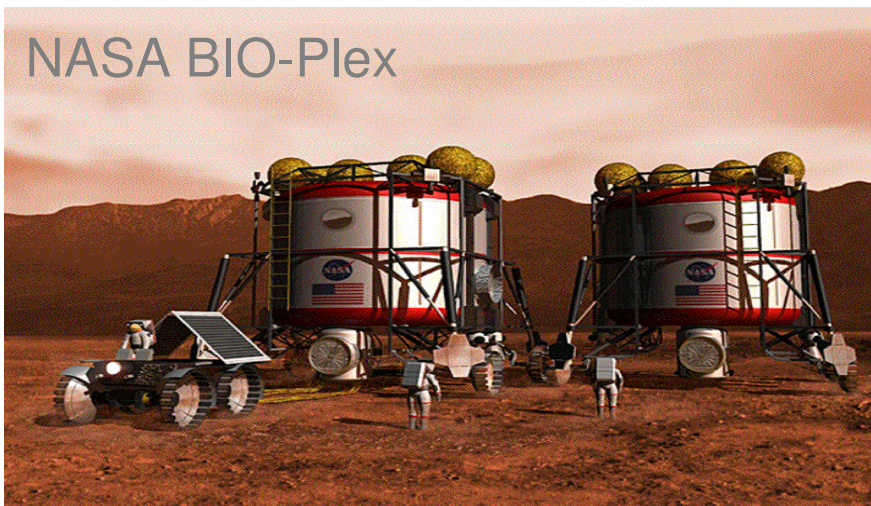
## DEMONSTRATION:



## Mars Entry, descent & Landing

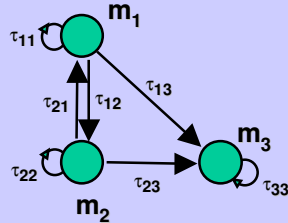
# A Hybrid Discrete/Continuous System for Health Management

- Failures can manifest themselves through a coupling of a system's continuous dynamics and its evolution through different behavior modes  
 $\Rightarrow$  *must track over continuous state changes and discrete mode changes*
- Symptoms are initially subtle; on the same scale as sensor/actuator noise  
 $\Rightarrow$  *need to extract mode estimates from subtle symptoms*



Support:  
 • NASA IS

Hidden Markov Models



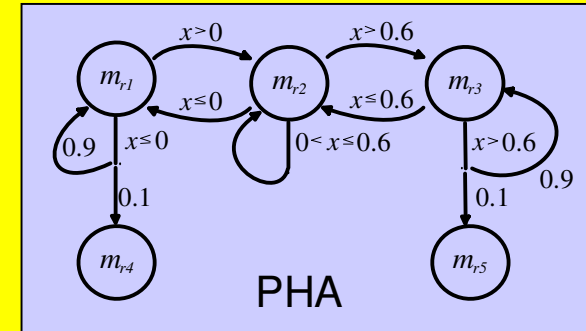
+

Continuous Dynamics

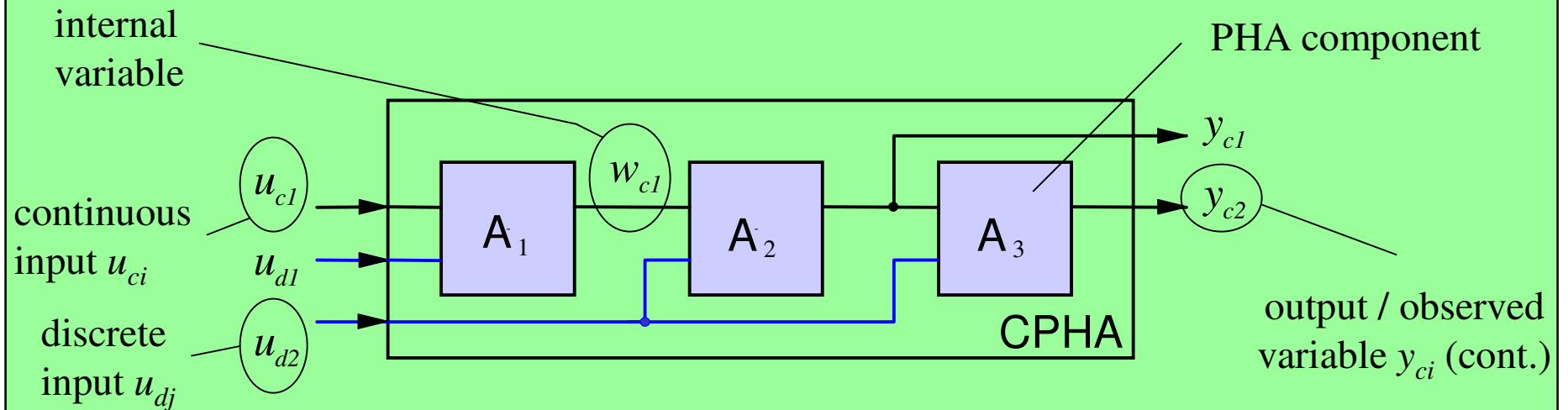
$$m_1: \begin{cases} x_c(k+1) = f_{c1}(x_c(k), u_c(k), v_c(k)) \\ y_c(k) = g_{c1}(x_c(k), v_c(k)) \end{cases}$$

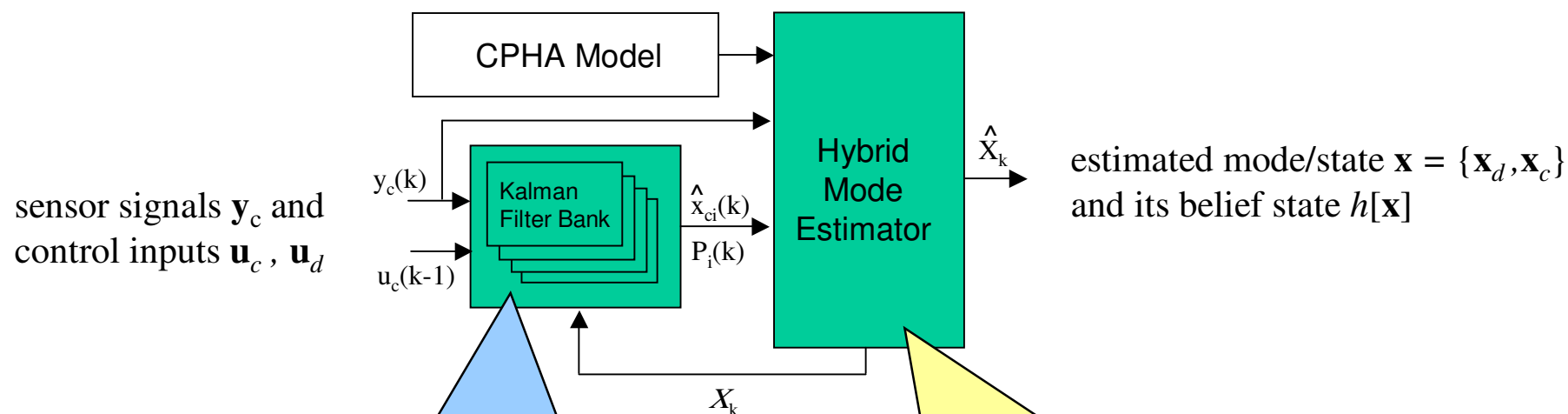
$$\vdots$$

$$m_i: \begin{cases} x_c(k+1) = f_{ci}(x_c(k), u_c(k), v_c(k)) \\ y_c(k) = g_{ci}(x_c(k), v_c(k)) \end{cases}$$



## Concurrent Probabilistic Hybrid Automaton (CPHA):





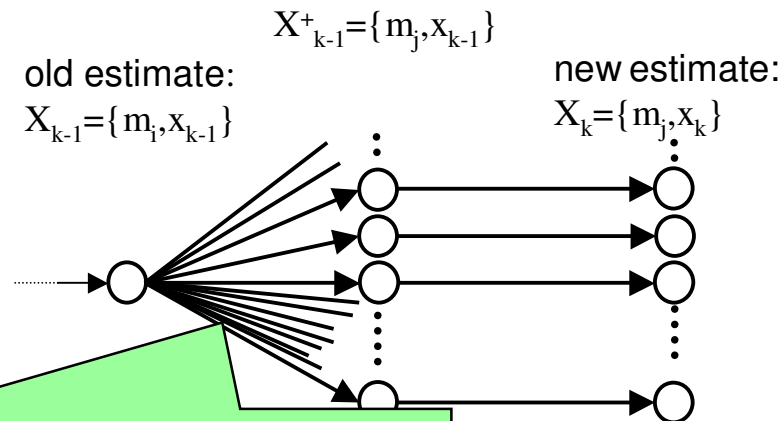
## Hybrid State Estimator

Maintains the set of most likely hybrid state estimates as a set of trajectories.

## Hybrid Mode Estimator:

Determines for each trajectory the possible transitions, and specifies (dynamically) the candidate trajectories to be tracked by the continuous state estimators.

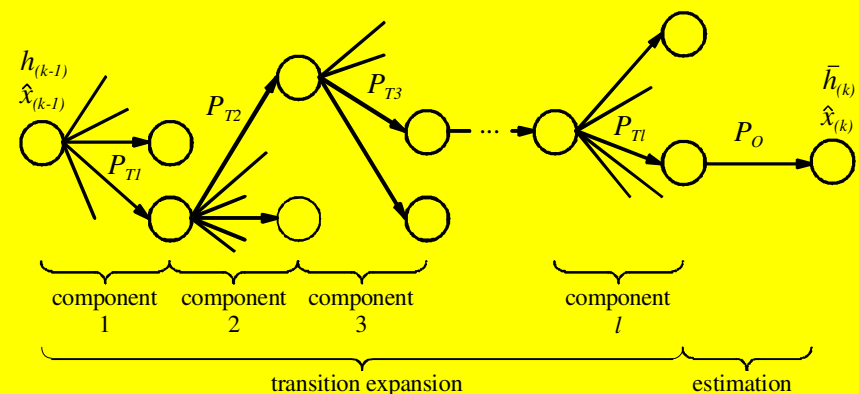
1. *HMM-style belief state update determines the likelihood for each discrete mode transition.*
2. *Kalman-filter-style update determines likelihood of continuous state evolution.*



# transitions at each time step is very large:  
e.g. model with 10 components, each with 3 successor modes  
has  $3^{10} = 59049$  possible successor modes for each trajectory!

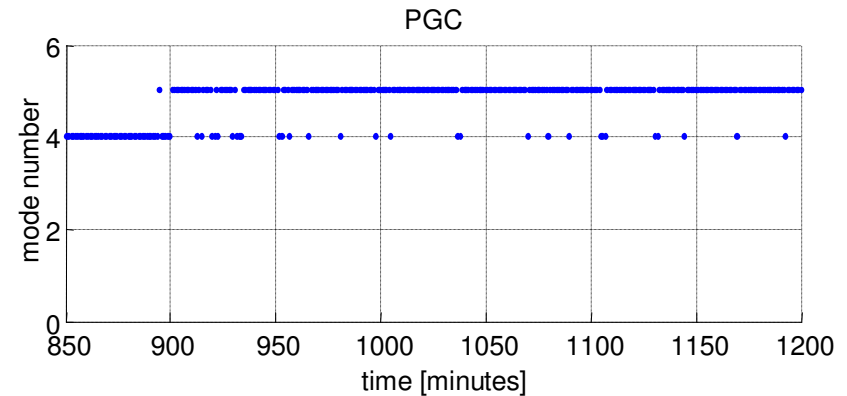
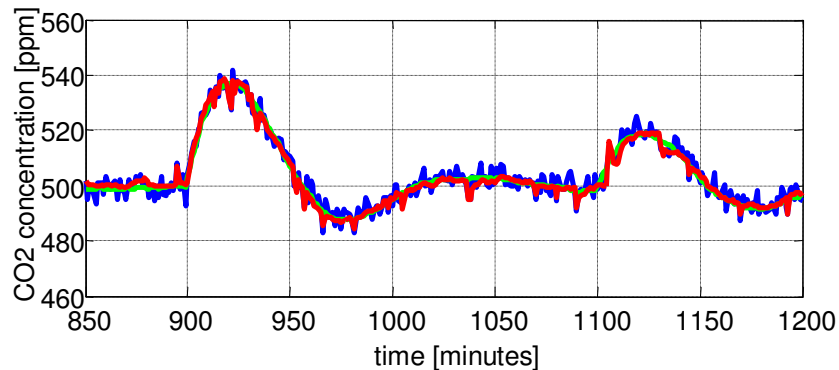
*How to handle the exponential blowup?*

- Generalize beam search to track the most promising hybrid states.
- Factor state space into lower dimensional subspaces through automated decomposition and filter synthesis.





# Simulation Result



components: 6

( FR1, FR2, PIV1, PIV2, LS, PGC)

total # of modes: 9600

fringe size: **20** (400 estimation steps):

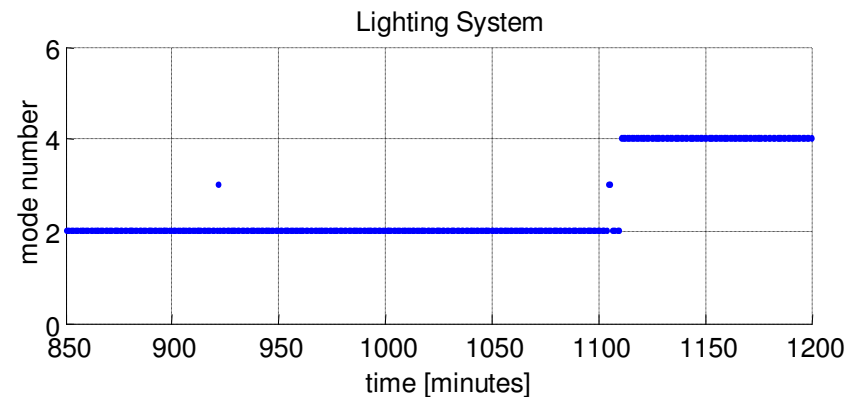
average candidates: 90.2 (< 1% !)

max. candidates: 428 (< 5 %!)

filter calculations: 242

filter executions: 36050

average runtime: ~1 s/step (PII-400, 128mb)





# Recent Publications

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## Hybrid Mode Estimation:

- Hofbaur, M. W. and B.C. Williams, “Mode Estimation of Probabilistic Hybrid Systems,” International Conference on Hybrid Systems: Computation and Control, March, 2002.

## Hybrid Expectation Maximization (preliminary):

- Melvin Henry, *Simulators that Learn: Automated Estimation of Hybrid Automata*, June 2002

## Hybrid Decomposition (preliminary):

- Hofbaur, M. W. and B. C. Williams, “Hybrid Diagnosis with Unknown Behavioral Modes,” International Workshop on Principles of Diagnosis, Austria, May 3-5 2002.



# Future Directions

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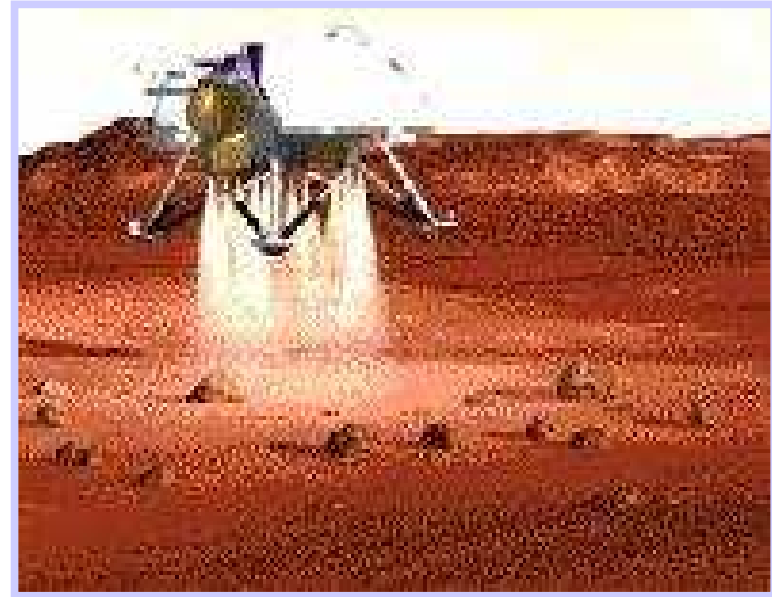
- Model-Learning as Hybrid EM
- Automated Decomposition of HPCA using Dissents
- Model-based Hybrid Execution



# To Address the Scope of Mars 98

## Polar Lander Leading Diagnosis:

- Legs deployed during descent.
- Noise spike on leg sensors latched by software monitors.
- Laser altimeter registers 50ft.
- Begins polling leg monitors to determine touch down.
- Latched noise spike read as touchdown.
- Engine shutdown at ~50ft.



Responding to the failures of Mars Polar Lander and Mars Climate Orbiter is a Hybrid control problem.

Idea: Support programmers with embedded languages that avoid commonsense mistakes, by reasoning from hardware models.



**Reactive Model-based Programming**

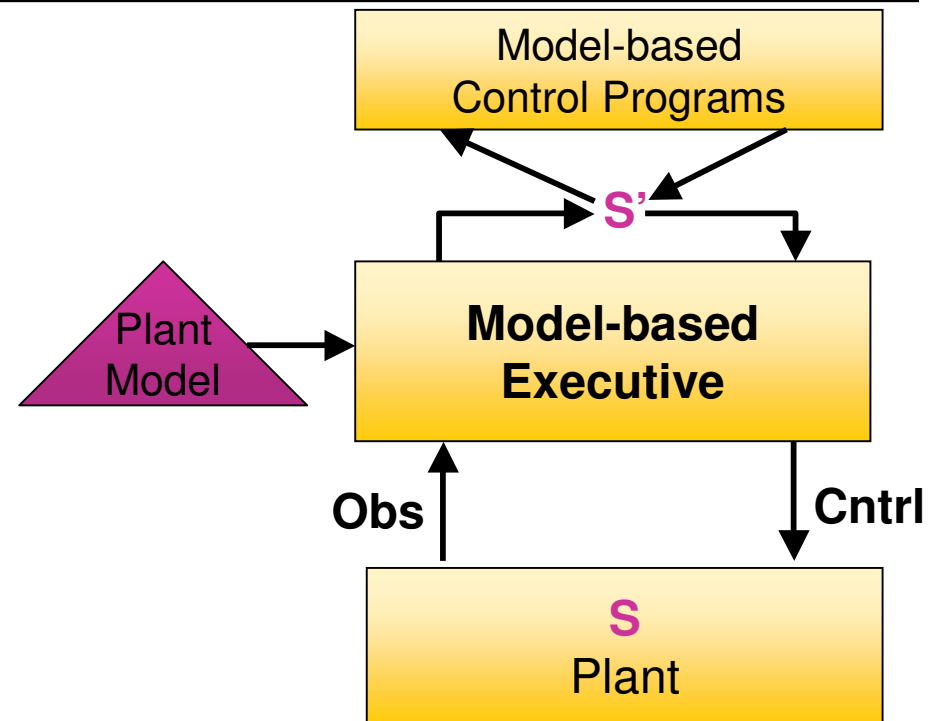


# Hybrid Model-based Programming



## Hybrid Model-based Programs:

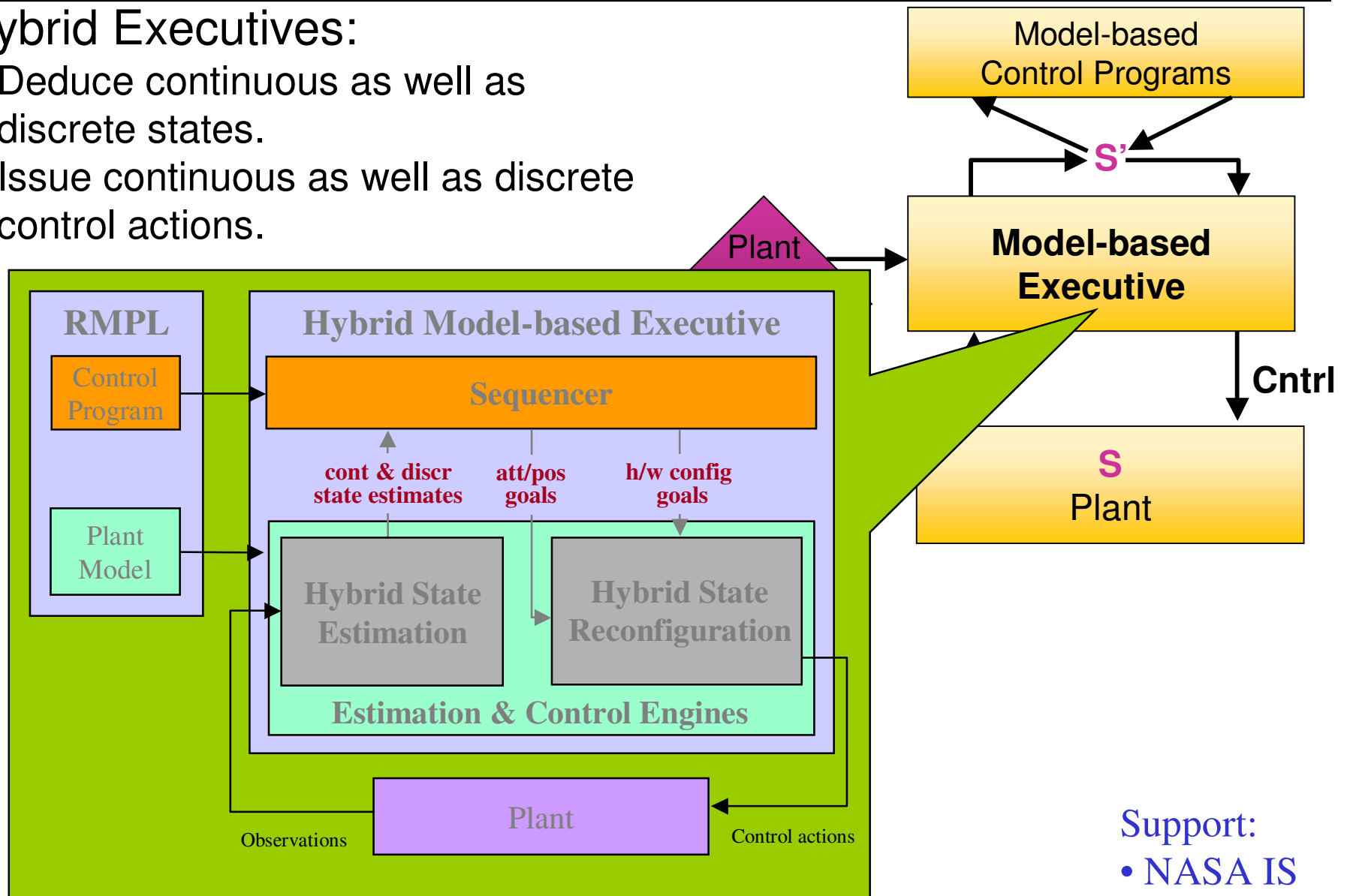
- Extend to include assertions and queries on continuous states.



Support:  
• NASA IS

## Hybrid Executives:

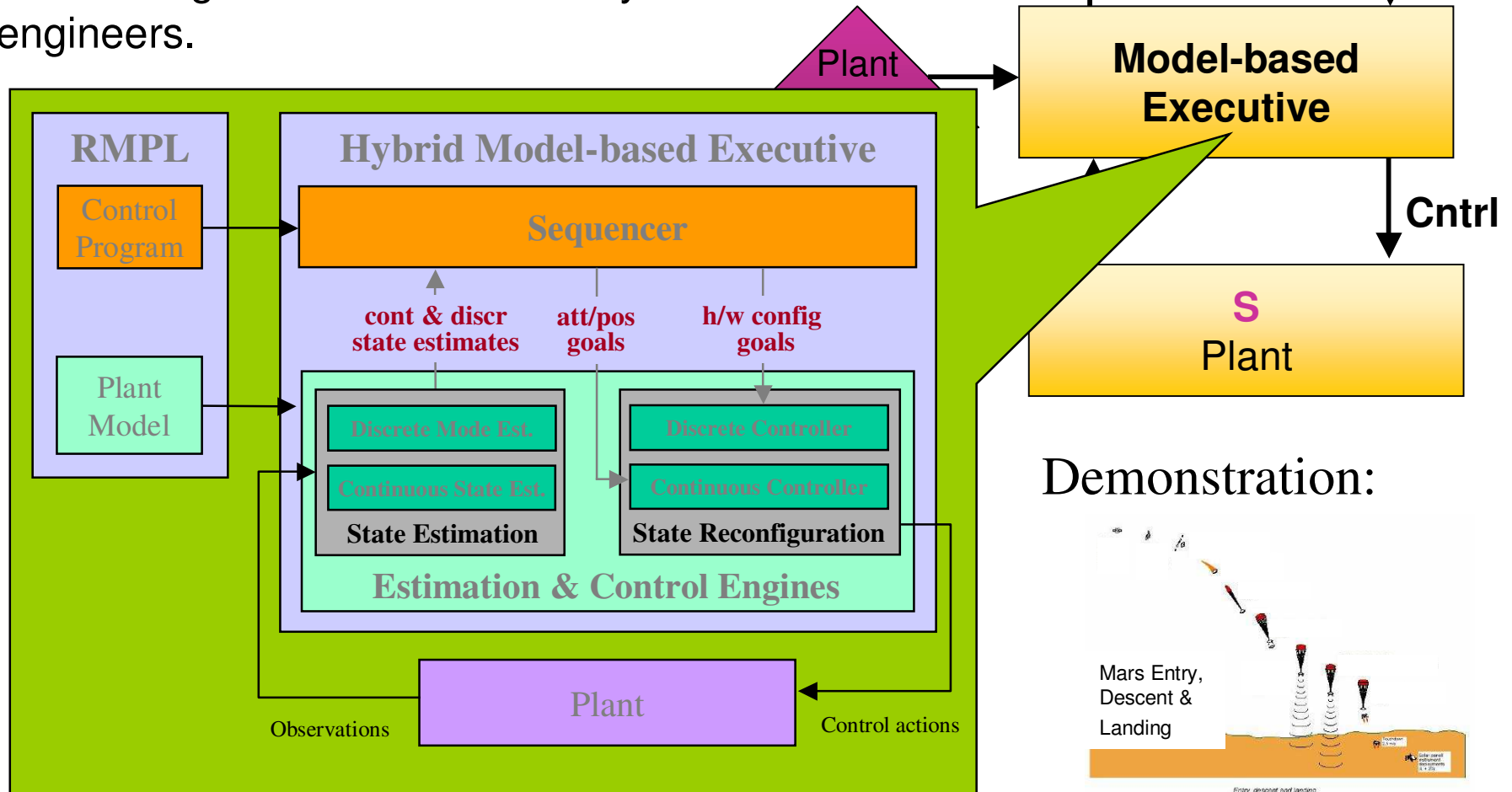
- Deduce continuous as well as discrete states.
- Issue continuous as well as discrete control actions.



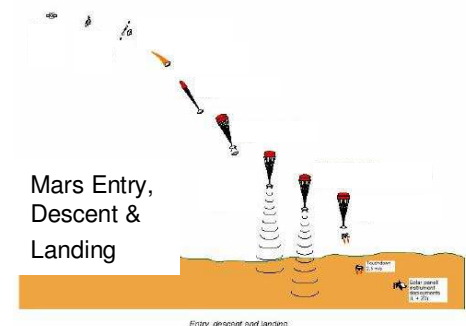
Support:  
• NASA IS

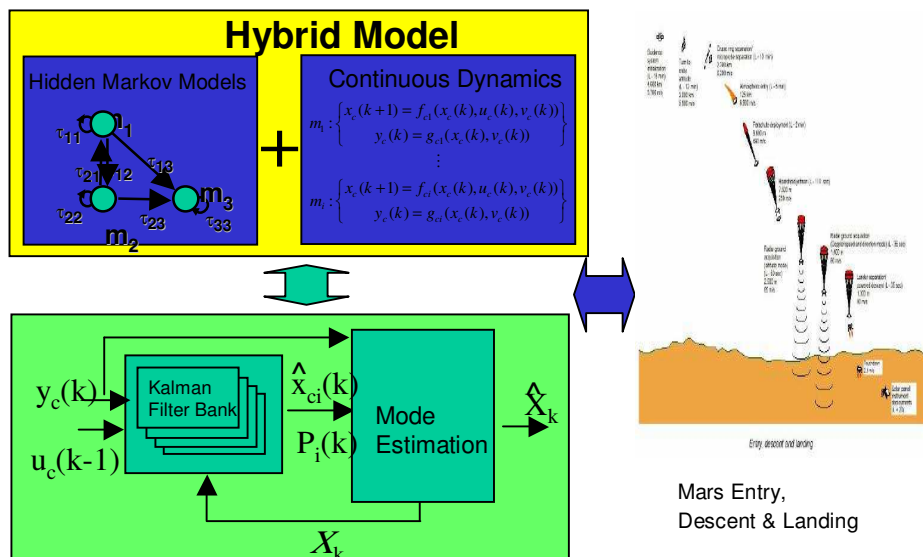
## Hybrid Executives:

- Can hook into existing estimation and control approaches.
- Should target “comfort zone” of systems engineers.



## Demonstration:





## TASK OBJECTIVES:

Create a hybrid monitoring, diagnosis and model learning capability for physical devices that exhibit complex discrete and continuous behaviors.

## TECHNICAL INNOVATIONS:

Dynamics are modeled as hybrid probabilistic concurrent automata (HPCA).

Monitoring, diagnosis, state tracking and model learning framed as elements of an Expectation Maximization algorithm for HPCA.

**SPONSOR:** NASA Code-R (Intelligent Systems)

**DEVELOPMENT TEAM:** MIT, JSC

Milestones	FY02	FY03	FY04
Hybrid Mode Estimation	X		
Learning as Hybrid Expectation Maximization		X	
Demonstration on Bioplex and Mars EDL		X	X
•Decomposition algorithms			X

## NASA RELEVANCE:

Recent mission failures (e.g., Mars Climate Orbiter and Polar Lander) highlight the need for monitoring capabilities that detect subtle symptoms, and simulators that can be quickly tailored to a mission. Our approach enables:

- predictive diagnosis and the detection of incipient failures that are hidden within noise.
- generation of estimators that track system state across changes in system modes.
- prototyping of simulators that acquire their physical models automatically.